A CONNECTED WORD RECOGNITION METHOD UTILIZING DTW AND A COARTICULATION MODEL

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ABSTRACT

Coarticulation is one of the major factors that make speech recognition difficult. In conventional connected word recognition methods, a template for a connected word sequence is made by simply concatenating the templates of a single word. Therefore, some misrecognitions occur on account of this disregard for coarticulation. This study examines the influence of coarticulation in concatenating templates. The boundaries between words are smoothed so as to incorporate the influence of the tail of the preceding word on the head of the following word. The results of recognition experiments of 35 tokens of 4-digit-sequences show a recognition rate improvement of 5%, giving an 98% correct recognition rate.

INTRODUCTION

The method of dealing with coarticulation in connected word recognition is important. A template for a connected word sequence is made by simply concatenating the templates of a single word by conventional methods utilizing DTW. However, the template is not continuous at word boundaries, and is not always suitable for reference patterns. By introducing the effect of coarticulation at word boundaries, the template would be made more suitable by smoothed discontinuity.

In order to smooth a boundary, the previous word must be determined, and it must be kept unchanged until the DTW for a word is completed. Therefore we have adopted two methods by which the previous word can be determined, and have tried to bring a coarticulation model into these algorithms. We have adopted a critically damped 2nd order linear system for our coarticulation model. We consider only the effect from previous words to following words in this model.

In this study, we used LPC cepstra as feature parameters. The speech signal was sampled at 10kHz and quantized into 12 bits. The speech signal was analyzed every 10ms (=frame) after differentiation to emphasize high frequency regions. A recognition experiment was done for 3 male speakers. Reference patterns were prepared for each speaker.

COARTICULATION MODEL

We adopted a critically damped 2nd order linear system for the coarticulation model. The step responses of the model are shown in Fig.1 for several time constants. In a discrete system, the response of the model is calculated according to equation (1) (ref 1).

\[ y(i+1) = (1-r)\cdot x(i+1) + 2r\cdot y(i) - r^2\cdot y(i-1), \]

where \( x(i) \) is the input and \( y(i) \) the output;
\( r = \exp(-T/\tau); T \) is the sampling period (namely the frame interval, 10 ms); and \( \tau \) is the time constant. Using this response, the coarticulation model modifies the reference patterns to connect each element of the feature sets smoothly to the previous reference (see Fig. 2).

The reference pattern \( R_k(j) \) of word \( k \) is modified as follows.

\[
\begin{align*}
R_k(1) &= (1-r)^2 R_k(1) + 2r R_{ks}(J_{tmp}) - r^2 R_{ks}(J_{tmp}-1) \\
R_k(2) &= (1-r)^2 R_k(2) + 2r R_k(1) - r^2 R_{ks}(J_{tmp}) \\
R_k(j) &= (1-r)^2 R_k(j) + 2r R_k(j-1) - r^2 R_{ks}(J-2) \quad : \text{for } j=3, \ldots, 10
\end{align*}
\]

where \( R_{ks}(j) \) is the reference pattern of the previous word \( ks \); \( J_{tmp} = J(ks) - J_{bk} \); \( J(ks) \) denotes the length of the word \( ks \).

In setting a large value to \( \tau \), the effect of the previous word \( ks \) becomes stronger, and at the limit of \( \tau \to 0 \), the effect disappears. We set \( \tau \) at 10 ms empirically.

\( J_{bk} \) specifies the start of the sampling position of the previous word. When sampling the feature parameters of the previous word \( ks \), the last frame \( R_{ks}(J(ks)) \) is not always suitable for reference, because the decrease in the speech power in the last portion causes instability of the feature parameters. Therefore, \( J_{bk} \) is used for sampling the stable portion returning from the tail \( J(ks) \) by \( J_{bk} \). We fixed \( J_{bk} \) at 5.

Fig. 2 Smoothing the word boundary

In the formula (2) and (3), the feature parameters of the previous word \( ks \) are carried over, so as to connect the word \( k \) smoothly to the word \( ks \). The modification is applied to the first 10 frames (0.1 s) of the word \( k \). Research on the modification range needs to be carried out in the future. The reference pattern \( k \) is modified when it is used. The modification has no influence on the original reference that is stored in a data file.

**METHOD 1: MODIFIED ONE-STAGE DYNAMIC PROGRAMMING ALGORITHM**

We put the previous word loop into one-stage dynamic programming algorithm (ref 2), and accumulated distances were calculated for each previous word (see Fig. 3).

When there is no previous word detected, the algorithm works as a one-stage DTW. Once \( j \) previous words have been detected, the starting part of each reference pattern is modified to connect the previous word smoothly. This smoothing is done according to the coarticulation model explained above.

The algorithm is the following.

1) Initialize \( D(0,j,k,ks)=0 \) and \( D(i,j,k,ks)=\infty \), for all \( i, j, k, ks \).
2) For $i = 1, \ldots, I$ do 3), 4), 5), 6), 7) and 8): test pattern frame loop
3) For $ks = 1, \ldots, K$ do 4), 5), 6) and 7): previous word loop
4) For $k = 1, \ldots, K$ do 5) and 6): word loop
5) For $j = 1, \ldots, J(k)$ do 6): reference pattern frame loop
6) $D(i, j, k, ks) =$ minimum of the accumulated distance among allowed DP paths
7) $TS(i, ks) = \arg\min(k = 1, \ldots, K) D(i, J(k), k, ks)$,
   $FS(i, ks) =$ starting point of $TS(i, ks)$
8) $T(i) = \arg\min(k = 1, \ldots, K) D(i, J(k), k, ks)$: $ks = 1, \ldots, K$, $F(i) =$ starting point of $F(i)$
9) Backtrace optimal word sequence reversely from $T(i)$ using $T(i)$ and $F(i)$

We have adopted DP paths including a slope constraint. DP paths are different for the boundary and for the inside. At word $k$ the boundary (i.e. $j = 1$), two transitions are allowed: $\alpha_0, \beta_0$ (see Fig. 4). Both $\alpha_0$ and $\beta_0$ refer to the accumulated distance of previous word $ks$, i.e.,

$$D(i, 1, k, ks) = \min \{ D(i - 1, J(k), ks, ks), D(i - 2, J(k), ks, ks) + \alpha_0 \}$$

where $ks1 = FS(i - 1, ks)$; $ks2 = FS(i - 2, ks)$; $C_I$ is the weight for the test pattern; $C_J$ is the weight for the reference patterns (we set $C_I$ at 1.0 and $C_J$ at 0.0); $d(i, j, k, ks)$ is the local distance between frame $i$ in the test pattern, and frame $j$ in the reference pattern $k$ preceded by the word $ks$.

When $ks$ is not detected, the accumulated distance terms (i.e. $D(*)$) are omitted. The transition $\beta_0$ is omitted when $i \leq 2$.

In the reference pattern $k$ (i.e. $j \geq 2$), three transitions are allowed: $\alpha$, $\beta$, $\gamma$ (see Fig. 5).

$$D(i, j, k, ks) = \min \{ D(i - 1, j - 1, k, ks), D(i - 2, j - 1, k, ks), D(i - 1, j - 2, k, ks) + \beta \}$$

When $ks$ is not detected, the accumulated distance terms (i.e. $D(*)$) are omitted. The transition $\gamma$ is omitted when $j = 2$, and $\beta$ is omitted when $i \leq 2$.

In the implementation of this algorithm, the range of the dimension $i$ was reduced to 3 because the algorithm needs the accumulated distances of recent 2 frames of the test pattern (i.e. 1-1 and 1-2).
METHOD 2: MODIFIED LEVEL-BUILDING DTW

We have developed a modified level-building DTW algorithm that searches for a quasi-optimal path between the test pattern and the optimal word sequence (ref 3). The DTW calculation of word \( k \) for level \( m \) is done from several starting points close to the optimal end point of each previous word (i.e., level \( m-1 \)), and the optimal end point for level \( m \) is determined (see Fig. 6). The end point of each word for level \( 0 \) is set at 0. For each previous word, the reference pattern is modified according to the coarticulation model.

RESULTS AND DISCUSSION

Table 1 shows the results of the tentative recognition experiment with METHOD 1 (ref 5). The data used in the experiment contain 35 tokens of 4-digit sequences that include all combinations of 2-digit sequences. Each digit has only one reading, therefore we prepared 10 reference patterns for all digits and one more for 'silence'.

The table shows that the coarticulation model improves the recognition rate. It is noticeable that the accumulated distance is decreased by applying the coarticulation model. This indicates that coarticulation processing is a promising method.

A major problem with this method is the amount of calculation involved. It can be reduced by omitting those words whose accumulated distances are larger than a predetermined threshold.

REFERENCE