HMM BASED FAST KEYWORD SPOTTING ALGORITHM WITH NO GARBAGE MODELS

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Abstract

The problem of discriminating keyword and non-keyword speech which is important in wordspotting applications is addressed here. We have shown that garbage models cannot reduce both rejection and false alarm rates simultaneously. To achieve this we have proposed a new scoring and search method for HMM based wordspotting without garbage models. This is a simple forward search method which incorporates the duration modelling of keyword for efficient discrimination of keyword and non-keyword speech. This method is computationally fast, which makes it suitable for real-time implementation. The results are reported on a speaker independent database containing 10 keywords embedded in 150 carrier sentences.

1 Introduction

Keyword spotting methods (KWS) using hidden Markov models (HMM) are based on continuous speech recognition (CSR) algorithms [1,2] where HMMs are used to model both keyword speech and non-keyword speech (comprising of background speech and non-speech sounds). The performance of these methods rely heavily on the performance of non-keyword speech models also known as "garbage" models. It has been shown [1,2] that by explicitly training garbage HMMs to model the entire background environment, the performance of the keyword spotting system can be improved. In most cases, garbage and keyword HMMs are connected as a network of HMMs and frame synchronous network (FSN) search method [3] is used to decode the test utterance into a sequence of garbage and keyword models. This approach is computationally complex and would be difficult for real-time implementation. The main difference between KWS algorithms is the way in which garbage models are defined and scoring methods are formulated.

2 Drawbacks of garbage modelling

The main aim of reducing the rejection rate and false alarm rate simultaneously cannot be achieved with garbage models. For a keyword to be recognised when it occurs in an utterance, we require

$$P(\mathbf{O}^i | \lambda_i) > P(\mathbf{O}^s | \lambda_g) \quad 1 \leq i \leq M \quad (1)$$

where λ_i = HMM of keyword - i , $\mathbf{O}^i$ = utterance of keyword - i , λ_g = garbage HMM and M = number of keywords in the vocabulary. To prevent false alarms, we need

$$P(\mathbf{O}^s | \lambda_g) > P(\mathbf{O}^s | \lambda_i) \quad 1 \leq i \leq M \quad (2)$$

where, $\mathbf{O}^s$ = garbage utterance. Since the non-keyword speech set is very large compared to the keyword set, the score for keyword and garbage utterances for garbage model will be comparable, i.e.,

$$P(\mathbf{O}^i | \lambda_g) \approx P(\mathbf{O}^s | \lambda_g) \quad 1 \leq i \leq M \quad (3)$$

Thus, the following relation becomes apparent from the above inequalities

$$P(\mathbf{O}^i | \lambda_i) > P(\mathbf{O}^i | \lambda_g) \approx P(\mathbf{O}^s | \lambda_g) > P(\mathbf{O}^s | \lambda_i) \quad (4)$$

The first inequality determines the number of rejections and the second determines the number of false alarms. The ML training of λ_i and λ_g [1,2] does not always assure the above inequalities. Even the on-line garbage modelling technique [4] could achieve low rejection rates at the expense of increased false-alarms. Inequality (4) also shows that garbage models cannot reduce rejection and false-alarm rates simultaneously, because, if we try to reduce $P(\mathbf{O}^i | \lambda_g)$ to achieve a lower rejection rate (inequality 1), this would also reduce $P(\mathbf{O}^s | \lambda_g)$ (relation 3) which would increase the false-alarms (inequality 2) and vice-versa. Thus both the rejection and false-alarm rates can be improved only by increasing the separation between $P(\mathbf{O}^i | \lambda_i)$ and $P(\mathbf{O}^s | \lambda_i)$ which shows that garbage models are not crucial for improving the performance of keyword spotters. Based on these arguments we propose a new technique of keyword spotting without garbage models.

3 No garbage model technique

Let K_i , $1 \leq i \leq M$ be the set of M distinct keywords and let λ_{K_i} be the corresponding keyword models. We denote the observation sequence corresponding to the utterance as $O (= O_1, O_2, \dots, O_T)$, T being the length of the utterance. Let $S_i(t_1, t_2)$ be the score for a keyword - i , $1 \leq i \leq M$, to occur in the observation interval from t_1 to t_2 , which is formulated as

$$S_i(t_1, t_2) = \frac{\log P_v(q^*_{t_1}, \dots, q^*_{t_2}, O_{t_1}, \dots, O_{t_2} | \lambda_i) + \log P_d(t_2 - t_1 | D_i)}{t_2 - t_1} \quad (5)$$

where P_v = Viterbi likelihood score, P_d = Duration probability for the keyword model D_i .

For the observation sequence $O_1, \dots, O_T$,

$$[i^*, t_1^*, t_2^*] = \arg \max_{i, t_1, t_2} S_i(t_1, t_2) \quad (6)$$

is determined for $1 \leq i \leq M$, $1 \leq t_1 \leq T$, $1 \leq t_2 \leq T$ such that $d_i^{\min} \leq (t_2 - t_1) \leq d_i^{\max}$ where $d_i^{\min}$ and $d_i^{\max}$ are the limits of the duration of keyword - i , estimated *a priori*. The

keyword i^* which maximizes $S_i(t_1, t_2)$ is the recognised keyword and t_1^* and t_2^* are the starting and ending locations.

3.1 Time Normalization

The log Viterbi probability, $\log P_v(q^*_1, \dots, q^*_L, O_1, \dots, O_L | \lambda_i)$ has a large value for short observation lengths and decreases monotonically for large observation lengths as shown in Figure 1. The log Viterbi probability being negative, this bias can be reduced by dividing it by the length of the observation sequence, $(t_2 - t_1)$. But experiments showed that, although time normalization works well for large observation lengths (i.e., remains more or less unbiased), it is unable to unbiased properly the log Viterbi probability for very short sequences. This is because, for very short length sequences the log Viterbi probability is so high that even duration normalization is ineffective.

3.2 Duration Modelling

To reduce the bias of the log Viterbi probability for short observation lengths a word duration penalty is introduced. The mean m_i and variance σ_i^2 , $1 \leq i \leq M$, of the duration of each keyword K_i , $1 \leq i \leq M$ are obtained from the training data. We fit a probability distribution, D_i , using the mean and variance as parameters. Gamma distribution is used as the probability density function, which has a range from $d = 0$ to ∞ , d being the duration random variable. The Gamma density falls off quite sharply to 0 as d decreases to 0, whereas it goes asymptotically to 0 as d tends to ∞ . The word duration penalty, $\log P_d(t_2 - t_1 | D_i)$ in equation (5) removes the bias of the log Viterbi probability for short length sequences without affecting the higher length sequences significantly. This can be seen from Figure 2, which plots the time normalized log Viterbi probability (a) and the score $S_i(t_1, t_2)$ (b) for the same values of $t_1 (= 43)$ and t_2 and for the same keyword model and for the same keyword utterance. From the figure 2(a), for the log Viterbi probability with time normalization there is a local maxima for $t_2 = 73$ (which is the correct ending point) but, this maxima is overshadowed by a maxima for a much short duration, for $t_2 = 56$ (duration being 14 observation symbols). It can be seen from the figure 2(b) that the score, $S_i(t_1, t_2)$ suppressed the spurious short duration peak and the maxima at $t_2 = 73$ is kept unaltered. Thus the word duration penalty, $\log P_d(t_2 - t_1 | D_i)$ promotes more probable durations and penalizes the less probable ones.

3.3 Algorithm

The complete algorithm is described below,

1. Get the observation sequence $O_1, \dots, O_T$ for a particular speech utterance.
2. Start with $i = 1, i$ being the keyword index
3. $t_1 = 1$
4. If $t_1 + d'_{\min} - 1 > T$, go to step 8.

5. Calculate $S_i(t_1, t_2)$ from the observation sequence $O_1, \dots, O_T$ and λ_i where

$$t_1 - d'_{\min} - 1 \leq t_2 \leq \min[T, t_1 + d'_{\max} - 1]$$

6. If $S_i(t_1, t_2)$ is maximum over all the keyword scores considered so far, store keyword index i and the time instants t_1 and t_2 .

7. $t_1 = t_1 + 1$, go to step 3

8. $i = i + 1$, go to step 3 for $2 \leq i \leq M$, M being the number of keywords.

After termination, the keyword which gave the maximum score, $S_{i^*}(t_1^*, t_2^*)$, $1 \leq i^* \leq M$ its starting (t_1^*) and ending locations (t_2^*) are obtained. Threshold score (S'_i) $1 \leq i \leq M$, for each keyword is estimated *a priori* using Baye's Minimum Error Criterion. If $S_{i^*}(t_1^*, t_2^*) \geq (S'_i)$, then the recognized keyword is i^* , else no keyword is present.

The above algorithm can be visualized as searching for a keyword within a window of observation sequence for each keyword model. The window is slid across the entire observation sequence. This is shown in Figure 3. The size of the window is determined by $d'_{\min}$ and $d'_{\max}$, $1 \leq i \leq M$. The search limits $d'_{\min}$ and $d'_{\max}$, $1 \leq i \leq M$ are set at $d'_{\min} = m_i - 0.5\sigma_i$ and $d'_{\max} = m_i + 3\sigma_i$.

By restricting the search within $d'_{\min}$ and $d'_{\max}$ we eliminate all garbage sequences outside this range from causing false alarms. For sequences within the allowed limit, the contrast between keyword and garbage is achieved by the Viterbi probability and the *a priori* duration weightage incorporated in the score. Thus, this method improves the separation between $P(O^i | \lambda_i)$ and $P(O^g | \lambda_i)$.

4 Experiment

Experiments are conducted on a ten keyword database (Indian city names, with at most one keyword per sentence), with each keyword modelled with a 5 state LR discrete HMM. Feature vector includes 10 weighted cepstral coefficients, energy, ratio of residual energy and zeroeth autocorrelation coefficient, zero crossing rate and delta energy. Vector quantization is done using a 256 size codebook designed using LBG algorithm. The recognition results and duration statistics are shown in Table - 1 and Table - 2 respectively. It is found from the experiments that the insertions usually have shorter durations than the expected keyword durations. It can be seen from Table - 3 that by restricting the lower search limit, $d'_{\min}$, keeping the upper limit $d'_{\max}$ and thresholds fixed, the false alarms have reduced significantly. Figure 4 gives the system performance for two values of $d'_{\min}$ as a function of threshold.

5 Conclusion

The major contribution of this paper has been to show that good keyword spotting performance can be obtained from an HMM system using no-garbage model. From the results we can see that the no-garbage model approach shows reasonably good recognition accuracy at a low false alarm rate. These

results can be compared with that of Rose [2], who has used very elaborate modelling of non-keyword speech. This technique is also computationally fast which makes it possible to do word-spotting in real time. The performance can be further improved by using discriminate techniques of keyword training for increasing the separation between $P(O^i|\lambda_i)$ and $P(O^k|\lambda_i)$.

6 References

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Figure 1. Variation of log Viterbi probability with time

(a)

Time normalized log Viterbi probability vs. Time

(b)

Time normalized log Viterbi prob. and Duration penalty vs. Time

Figure 2. Scoring scheme

Figure 3. Search method.

Figure 4. System performance as a function of thresholds for two values of d_i^{min}

Table 1. Results of No garbage model keyword spotting technique.

Data Set	No. of sentences	Detection Rate (%)	False Alarm Rate (FA/kw/hr.)
Train	250	96.80	2.66
Test	150	69.33	4.80

Table 2. Duration Statistics

Data Set	No. of sentences	Mean error in start pt.	Mean error in end pt.	Error variance in start pt.	Error variance in end pt.
Train	250	2	2	5.52	11.33
Test	150	2	2	7.19	10.88

Table 3. Recognition performance for test data for variable d_i^{min}

d_i^{min}	Recognition rate (%)	False Alarm Rate Fa/Kw/Hr
$m_i - 0.25\sigma_i$	65.33	4.20
$m_i - 0.5\sigma_i$	69.33	4.80
$m_i - 0.75\sigma_i$	68.00	4.80
$m_i - \sigma_i$	68.67	5.40
$m_i - 2\sigma_i$	68.00	9.00
$m_i - 3\sigma_i$	68.00	9.00
$m_i - 4\sigma_i$	68.00	9.00
$m_i - 5\sigma_i$	68.00	9.00