THE BBN SINGLE-PHONETIC-TREE FAST-MATCH ALGORITHM

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ABSTRACT
In this paper we present a very fast and accurate fast-match algorithm which, when followed by a regular beam search restricted within only the subset of words selected by the fast-match, can speed up the recognition process by at least two orders of magnitude in comparison to a typical single-pass speech recognizer utilizing the Viterbi (or Beam) search algorithm. This is a novel fast-match algorithm that has two important properties: high-accuracy recognition and run-time proportional to only the cube root of the vocabulary size.

1. INTRODUCTION
In January 1993, at a DARPA workshop held at MIT, BBN demonstrated for the first time ever a real-time, 20K-word, speaker-independent, continuous speech recognition system, implemented in software on an off-the-shelf workstation. One part of the algorithm was published soon thereafter [1]. However, the fast-match part of the algorithm, which has recently received a US patent [2], has not been described until now.

While a number of fast-match algorithms have been published, the BBN algorithm continues to have novel features that have not appeared in the literature. The fast-match algorithm has two important properties: high-accuracy recognition and run-time proportional to only the cube root of the vocabulary size.

In this paper, the vocabulary is organized as a phonetic tree similar to Ney's [3]. However, in contrast to prior approaches in which several copies of the trees are needed in order to use a word bigram language model, the innovation in this algorithm allows us to use a word bigram language model with just a single phonetic tree. In the remainder of the paper, we will present in detail how we construct such a phonetic tree and how to estimate the acoustic and language models. Then we will explain the search algorithm and report our findings about the computational requirements.

2. PHONETIC TREE
Assume a vocabulary that consists of the following three words, 'abc', 'abcd', and 'ade' whose phonetic pronunciations are a-b-c, a-b-c-d, and a-d-e respectively. The phonetic tree for this vocabulary can be constructed as illustrated in Figure 1. The annotations next to the nodes are the composite triphones of the phonemes associated with the nodes. For example, &a;[ab] denotes a composite triphone for phoneme 'a' whose left context is the boundary with the special symbol '&', and right context is phonemes 'b' or 'd'. That is, the special triphone &a;[ab] is a composition of two normal triphones &a;[a]b and &a;[a]d. All other nodes can be interpreted in the same manner, for example, &c;[cd] is a composite triphone for phoneme 'c' whose left context is phoneme 'b' and right context 'd'.

There are probably some unique characteristics of this type of phonetic tree in comparison to other types of lexical trees studied before, such as that of Ney's [3]. First, the phonemes are associated with the nodes rather than the arcs of the tree. Second, the last phoneme node of each word is kept unique, even if the word is a substring of another word. Third, each node in the tree is associated with a set id representing the set of words which share this node. The last two characteristics of this type of phonetic tree make it possible to use a word bigram language model during the search without tree copying.
3. ACOUSTIC MODELS

With the phonetic tree constructed as in Figure 1 where each
node represents a (possibly shared) triphone, the acoustic
model for the composite triphone associated with that node
can be approximated as a weighted average of the corre-

sponding normal triphones. For a Tied Mixture (TM) or
Phonetically-Tied Mixture (PTM) or State-Clustered Tied-
Mixture (STM) model [4], the correspondent normal tri-
phones share the same codebook (i.e. a Gaussian mixture)
whereas their mixture weights are separate. Then the com-
posite triphone would use that same codebook and its mix-
ture weights are the weighted average of the mixture weights
of the correspondent normal triphones. For example, the mixture weight $v_i^x$, for component $j$ of the Gaussian
mixture for composite triphone $&[a]b,d$ is calculated as:
\[ v_i^x = \frac{v_j^x a b + v_j^x a d}{c_i^x a b + c_i^x a d} \]

where $v_j^x$ stands for the mixture weight for component $j$ of the normal triphone $x$ and $c_i^x$ stands for the EM (training)
count of the normal triphone $x$.

4. LANGUAGE MODELS

In the same manner as done for the acoustic models, we can
approximate a bigram language model for these nodes as
well. In contrast to previous approaches where the language
bigram probability is applied either at the first phoneme or
the last phoneme node with some form of tree copying, our
algorithm allows us to apply the language probability cu-
umatively over all composite triphone nodes in the words
in the single tree. Assume the same phonetic tree as in Fig-
ure 1, and some word $w$ has just ended, we want to apply
the probability of going into node $&[a]b,d$. Since all three
words, ‘abc’, ‘abcd’, and ‘ade’ share this node, the probabil-
ity of going into node $&[a]b,d$ given the preceding word $w$
would be
\[ Pr(&[a]b,d|w) = Pr(abc|w) + Pr(abcd|w) + Pr(ade|w). \]

Similarly,
\[ Pr(a[b]c|w) = Pr(abc|w) + Pr(abcd|w), \]
\[ Pr(b[c]d|w) = Pr(abc|w), \]
\[ Pr(b[c]d|w) = Pr(c[d]|w) = Pr(abcd|w), \]
and
\[ Pr(a[d]|w) = Pr(d[e]|w) = Pr(ade|w). \]

We call this language model a composite set bigram model
since it is the collection of the conditional probability of a set
of words that share a composite triphone given a preceding
word. Note that, since the last phonemes of the words are not
shared, the sets associated with the leaves are singletons
(i.e. sets which consist of a single member). Consequently,
the conditional probability of the set at the last phoneme of
a word given a preceding word is just the usual word bigram
probability.

The lower-order composite set ngrams (i.e. the set unigrams)
can also be approximated in the same manner.

To say it another way, the composite set bigram language
model used in this fast-match is a different representation
of the usual word bigram language model with some additions.
First, the usual $Pr(w_i|w_j)$ now becomes $Pr(|w_i|w_j)$, where
$\{w_i\}$ is the singleton set that consists of only $w_i$. $Pr(w_i)$
becomes $Pr(|w_i|)$. For some set $\{w_i\}$ which includes more
than one member, $Pr(|w_i|w_j) = \sum_{w_k \in \{w_i\}} Pr(w_k|w_j)$.
And $Pr(|w_i|) = \sum_{w_k \in \{w_i\}} Pr(w_k)$.

5. THE SEARCH ALGORITHM

The search algorithm is similar to the time-synchronous
beam search [5] with a small addition to use the compo-
site set bigrams. Again, assume the same phonetic tree as
before, at some time $t$, some $k$ words end. Let $\alpha^t_i$ be
the partial path score from the beginning of the sentence up
to word $w_i$ at time $t$, node $&[a]b,d$ will be activated with
the product score
\[ s = \arg \max_{1 \leq i \leq k} \{ \alpha^t_i \ast Pr(&[a]b,d|w_i) \}. \]

That is, we search over the $k$ ending words for the best word
to go into node $&[a]b,d$. The value of $s$ and the time $t$ are
then associated and carried along with node $&[a]b,d$ during its
duration. At some time $t_2$ frames later, with an exit score $s'$,
$&[a]b,d$ will activate $a[b]c$ and $a[d]e$ with the products
\[ u = \arg \max_{1 \leq i \leq k} \{ \alpha^t_i \ast Pr(a[b]c|w_i) \} \ast \frac{s'}{s} \]
and
\[ v = \arg \max_{1 \leq i \leq k} \{ \alpha^t_i \ast Pr(a[d]e|w_i) \} \ast \frac{s'}{s} \]
respectively. Note that, we still search over the same $k$
ending words at time $t$. Both $a[b]c$ and $a[d]e$ carry along with
them the time $t$, and the values $u$ and $v$ respectively.
Note that the division $s'/s$ in effect takes out the temporary
composite bigram $Pr(&[a]b,d|w_i)$ used in the preceding
node. This is the case since $s'$ is the product of $s$ and the
acoustic score for node $&[a]b,d$ from time $t$ to time $t + t_1$.

Then after some $t_2$ frames later, assume that node $a[b]c$ ends
with an exit score $u'$. In turn, $a[b]c$ will activate $b[c]d$ and
$b[c]d$ with the products
\[ p = \arg \max_{1 \leq i \leq k} \{ \alpha^{t+1}_i \ast Pr(b[c]d|w_i) \} \ast \frac{u'}{u} \]
and
\[ q = \arg \max_{1 \leq i \leq k} \{ \alpha^{t+1}_i \ast Pr(b[c]d|w_i) \} \ast \frac{u'}{u} \]
respectively.

Recall that by the design of the phonetic tree, the com-
posite set associated with the node representing the last
phoneme of the word is a singleton set. So, for node \(b[c]\),
\[ Pr(b[c]\mid w_i) = Pr(abc\mid w_i) = Pr(abc\mid w_i). \]
Consequently, the search algorithm really uses a true word bigram language model when it reaches the last phoneme of the word. All other set bigrams used for the interior nodes could be considered as partial or temporary language model scores. The gradual amortization of the language model score makes pruning much more efficient and robust.

Eventually, node \(b[c]\) will end, say at \(t_3\) frames later, and the search will cycle back to the propagation mentioned in Equation 1 for the root node of the phonetic tree with a new value \(s'_{t+1} + s + b\). As reflected in Equation 1, the word bigram \(Pr(b[c]\mid w_i)\) is not taken out (as those composite set bigrams at the interior nodes are, through the division \(s'/s\) and \(u'/u,\) etc.).

In general, the propagation of theories on this phonetic tree is quite similar to that of a beam search on a linear lexicon, except for the addition of the adjustment of the composite set bigrams when approaching a phoneme node: To activate a node, we temporarily use some composite bigram probability; to leave that node, we remove that temporary bigram probability. The closer the search approaches the end of the word, it uses a more complete bigram probability.

5.1. Normalized Forward-Backward

As described in [6], the only goal of this fast-match is to keep the likely word endings and their partial scores to guide the second pass. This can be simply done by maintaining a list of words ending at each frame and their partial scores. At each time frame, we record the score of the final state of each word ending. Let \(\Omega^t\) be the set of words ending at time \(t\), and \(\alpha_{t}^1\) be the partial path score up to word \(w_i\) at time \(t\). Each \(\alpha_{t}^1\) represents the probability of the speech from the beginning of the utterance up to time \(t\) given the most likely word sequence ending with word \(w_i\) times the probability of the language model for that word sequence.

As described in [7] and [8], the second backward pass is essentially the time-synchronous beam search. When some word \(w\) ends at some time \(t\) with a partial score \(\beta_{t}^2\) (\(\beta\) is similar to \(\alpha\) in the forward pass but from the end of the utterance up to \(w\)), instead of activating the whole lexicon as in the linear lexicon beam search, we only activate those words \(w_i \in \Omega^{t-1}\) if they satisfy the following condition:

\[
\frac{\alpha_{t-1}^2}{\max \alpha_{t-1}^2} \cdot \frac{\beta_{t}^2}{\max \beta_{t}^2} \cdot Pr(w_i\mid w, w_j) > \gamma
\]

where \(w_j\) is the best ‘preceding’ word of \(w\), and \(\gamma\) is the forward-backward pruning threshold.

5.2. Admissibility

The fast-match algorithm is clearly not admissible in a strict sense. However, although the best result from the fast-match is not as accurate as the full search, we find in very large studies that it never causes increased error for the second pass.

5.3. Efficiency Issues

It is possible to make the fast-match run as fast as possible provided that it can save sufficiently good words ending at each frame for the second pass. We typically save about 100 words. The first thing that can speed up the search is to minimize \(k\) in Equation 1 (This also helps all the other \(\arg max\), \(\arg max\), \(\arg max\) evaluation as well). Right after saving these \(k\) words to guide the second pass later, this list can be truncated to leave only a few high-score words. Empirically, we observed that for a 20000-word demo system, \(k\) can be 4 or 5.

Another part of the computation that takes a long time is the access to the bigram probabilities, since these are normally stored in a compact representation. To avoid this, we establish a bigram cache for a few active states (ending words). For each of these states, we have a random access array of all of the bigram probabilities.

We can also save computation by not evaluating \(\arg max\), \(\arg max\), \(\arg max\) \(Pr(\text{a new destination node}\mid w_i)\) when the set id of the new destination node is the same as that of the source node. Instead, we use the same result evaluated when going into the source node before. This can be detected easily by checking if there is only one out arc from the source node. This is true since, from the design of the phonetic tree, if there is only one out arc at a node, the destination node has the same set id as the source node.

6. COMPUTATION VERSUS VOCABULARY SIZE

To learn how the computation of this search strategy (fast-match followed by a trigram Forward-Backward beam search) [9]) grows with vocabulary size, we measured the computation required at three different vocabulary sizes: 1500 words, 5000 words, and 20000 words. The time required, as a fraction of real time, is shown plotted against the vocabulary size in Figure 2. As can be seen, the computation increases very slowly with increased vocabulary.

To understand the behavior better, we plotted the same numbers on a log-log scale in Figure 3. Here we can see that the three points fall neatly on a straight line, leading us to the conclusion that the computation grows as a power of the vocabulary size. Solving the equation gives us the formula

\[
time = 0.03V^{1/3}
\]

where \(V\) is the vocabulary size.

This is very encouraging, since it means that if we can decrease the computation needed by a small factor, it would be feasible to increase the vocabulary size by a larger factor, making recognition with very large vocabularies possible.
As a matter of fact, a year later in 1994, after some code optimization, this search strategy could run in less-than-real-time with a 40000 word vocabulary.

7. SUMMARY

We have described a novel fast-match algorithm based on a single phonetic tree. There are some unique characteristics in this proposed lexical tree which made it possible to use a word bigram language model during the search without tree copying. On this phonetic tree, all the last phonemes of the words in the lexicon always locate at the leaves of the tree. Each node of the tree is assigned a set id representing a group of words which share this node. The acoustic phoneme models associated with the nodes are the composite triphones where there could be more than one right context. In comparison to the usual triphone models, there is only a small difference for these composite triphones: the mixture weights of the composite triphones are the weighted average of the correspondent triphones. We also showed the transformation of the usual word bigram language model into a composite set bigram language model. With this composite set bigram language model, we could apply the language probabilities in a cumulative fashion at every phoneme node of the word without tree copying. The search itself is quite similar to the usual time-synchronous beam search with one addition: to activate a node, we temporarily use some composite bigram probability; to leave that node, we take out that temporary bigram probability. The fast-match can run as fast as possible provided that it can save sufficiently good words ending at each frame to guide the second pass. Finally, we demonstrated that the computation required by this algorithm grows as the cube root of the vocabulary size, which means that real-time recognition with very large vocabularies is feasible.

Acknowledgements

This work was supported in part by the Defense Advanced Research Projects Agency and monitored by Ft. Huachuca under contract No. DABT63-94-C-0063. The views and findings contained in this material are those of the authors and do not necessarily reflect the position or policy of the Government and no official endorsement should be inferred.

8. REFERENCES