Syntactic Error Modeling and Scoring Normalization in Speech Recognition
Final Report:
Error Modeling and Scoring Normalization in the Speech Recognition Task for Adult Literacy Training

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Preface

This research was conducted under auspices of the Research Institute for Computing and Information Systems by Lex Olorenshaw and David Trawick of Speech Systems Incorporated. Dr. Glenn Freedman served as RICIS research coordinator.

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The views and conclusions contained in this report are those of the authors and should not be interpreted as representative of the official policies, either express or implied, of NASA or the United States Government.
Error Modelling
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by

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1. Introduction

The purpose of the project was to develop our speech recognition system to be able to detect speech which is pronounced incorrectly, given that the text of the spoken speech is known to the recognizer. This is to be used by the staff at NASA-JSC to incorporate this technology into a "Literacy Tutor" multi-media system. The Literacy Tutor will also utilize other new technologies (such as video input) in order to bring innovative methods to the task of teaching adults to read.

2. Overview of Technical Objectives

The technical objectives of this project were as follows:

1) Develop our system so that when an isolated word is pronounced incorrectly, the recognizer will reject it. The expected word is known to the recognizer before decoding begins.

   Example-1a:
   
   SYSTEM PROMPTS: say this word - "cat".
   SPEAKER SAYS: [kæt] ("cat").
   SYSTEM RESPONDS (AUDIO): pronounced correctly.

   Example-1b:
   
   SYSTEM PROMPTS: say this word - "cat".
   SPEAKER SAYS: [kout] ("coat").
   SYSTEM RESPONDS: pronounced incorrectly.

2) Investigate how our system can provide information/feedback as to which part/phoneme(s) of an incorrectly pronounced word has been pronounced poorly.

   Example-2:
   
   SYSTEM PROMPTS: say this word - "cat".
   SPEAKER SAYS: [kout] ("coat").
   SYSTEM RESPONDS: "pronounced incorrectly. [æ] was poorly pronounced (as [ou])."

We felt that if our system could reliably accomplish these two tasks, it would provide a very valuable tool to the Literacy Tutor. Further utility of the speech recognizer would come as result of accomplishing the following objectives:

3) Develop our system so that when a multi-word utterance is spoken incorrectly into the recognizer, the system can reject it as being pronounced incorrectly.

   Example-3:
4) Investigate how our system can provide information/feedback as to which word of an
incorrectly pronounced utterance has been poorly pronounced.

Example-4:

SYSTEM PROMPTS: say this sentence - "the cat says meow".
SPEAKER SAYS: [ø kout sæz miaw] ("the coat says meow")
SYSTEM RESPONDS: sentence pronounced incorrectly. "cat" was poorly pronounced.

5) As an extension of objectives 2) and 4), investigate how our system can provide
information/feedback as to which phones within incorrectly pronounced words (within
an incorrectly pronounced utt) have been poorly pronounced.

Example-5:

SYSTEM PROMPTS: say this sentence - "the cat says meow".
SPEAKER SAYS: [ø kout sæz miaw] ("the coat says meow")
SYSTEM RESPONDS: sentence pronounced incorrectly. The word "cat" was poorly
pronounced. (Within the word "cat") [æ] was poorly pronounced (as [ou]).

As a result of the work performed on this project, we were able to achieve success in all but
the fifth objective.

3. Methodology

The proposal had proposed two methods for performing this work. The first method was
titled "Syntactic Error Modelling"; the second was "Score Normalization". After the
contract began, we also began to investigate a third method to achieve our objectives,
"Phoneme Error Modelling". Each of these methods is described briefly in the sections
below.

3.1 Syntactic Error Modelling

The original purpose of this project was to provide a quick and easy way for our system to
accomplish objective 1. It was thought that if the types of reading errors that are made
can be modelled as word errors (e.g. "cat" pronounced as "coat"), then the syntax can
provide a way for errors to be detected by the recognizer. The success of this error-
modelling technique depended on: 1) how many of the errors made can be modelled as
word errors, and 2) how well our recognizer can distinguish the word errors.

We had some experience with this approach in research performed on "keyword spotting".
In the keyword task, the speech recognizer tries to isolate only those words which are
thought to have some key meaning. The developer provides a list of keywords to be
recognized, as well as a list of potential non-keywords. When a sentence of speech is input
into the system, the recognizer attempts to filter keywords from non-keywords, and then
display the keywords which were recognized.

This is similar to syntactic error modelling in that for each word a student will read aloud
into the recognizer, we would like to have a listing of words which are often spoken as
mispronunciations of the prompted word. This list of words we call miscue words. The
recognition system can utilize this information as it tries to determine whether or not the student read the word(s) correctly. By knowing the potential errors that the student makes, the recognizer can consider the potential sequences of phonemes which may have been spoken, even if the word has been mispronounced as another word.

3.1.1 Activities

An outline of the tasks for this method is presented below. It was necessary to create a comparison case to measure the effectiveness of using real world word errors. This was done initially by randomly choosing a set of words to act as the miscue words.

For objective 1:

1) Define/design a test case for isolated word recognition
2) Investigate what the possible word errors are for the test case.
3) Collect test data
4) Create syntaxes using the potential word errors as miscue words.
5) Test the performance of the system for correct hits, correct rejections, incorrect rejections, etc.
6) Create syntaxes using randomly chosen words as miscue words.
7) Test the performance of the system for correct hits, correct rejections, incorrect rejections, etc.; compare results with above tests which used real world word errors.

For objective 2:

8) Examine the results to see how well the system performed in choosing a correct transcription from all possible miscue words to match an incorrectly pronounced word.

For objective 3:

9) Define/design a test case for utterance recognition
10) Investigate what the possible word errors are for the test case.
11) Collect test data
12) Create syntaxes using the potential word errors as miscue words.
13) Test the performance of the system for correct hits, correct rejections, incorrect rejections, etc.
14) Create syntaxes using randomly chosen words as miscue words.
15) Test the performance of the system for correct hits, correct rejections, incorrect rejections, etc.

For objective 4:

16) Examine the results to see how well the system performed in choosing any miscue word to align with an incorrectly pronounced word.

For objective 5:

17) Examine the results to see how well the system performed in choosing a correct transcription from the miscue words to match an incorrectly pronounced word.
3.2 Score Normalization

The original proposal contained an explanation of the "Score Normalization" project which would be done to get the recognizer to produce decoding scores which would approximate "goodness of pronunciation" judgements of humans. In other words, scores output by the decoder could produce better confidence thresholds to correctly reject mispronounced words. For example, if the user/student says the word "cat" as /kaet/, you would like the word and/or utt score to be such that it would always be above some rejection threshold. On the other hand, if the user/student says the word "cat" as /koat/, you would like the word and/or utterance score to be such that it would always be below some rejection threshold. "Score Normalization" was conceived as being a way to have the scores be reliable for accurate acceptance/rejection.

During the process of decoding the input speech, the Phonetic Decoder produces scores for the words it is considering. The word sequence with the highest total score is chosen as the output word sequence. The score of a word is a measure of how well some portion of the input speech matched with the Decoder's internal model of that word. Thus it seemed reasonable that this score (in some form) could be used to evaluate the quality of the pronunciation of a word.

However, these scores previously were not normalized. That is, the distribution of the scores was different for different words. The most obvious difference among scores for different words stemmed from the word length. Longer words have more terms in their scores, on the average, than shorter words. This made the scores of short and long words incomparable. Also, some phonemes are better recognized than others, which makes the scores for words with well recognized phonemes have a higher potential than the scores for words with poorly recognized phonemes.

The Decoder avoids most of these problems by only comparing scores corresponding to the same range of the speech input. This could not be done in a pronunciation evaluation application, because we have to be able to compare different instances of the same word (and different words), that is, different speech input, on some comparable scale.

Score normalization sought a way to normalize the scores for different instances of different words, so that they would be comparable in an absolute sense, rather than in the relative sense that they were previously. Better scores would then correspond to better matches with internal word models, which would in turn correspond to better word pronunciations.

3.2.1 Activities

We proposed a six step process for preparing a scoring normalization technique:

1) Measure the nature of the word score distributions.
2) Analyze the phenomena creating the differences among these distributions.
3) Prepare a normalizing method addressing the known differences.
4) Implement the normalizing method.
5) Test the normalizing method.
6) Depending on the results from these preliminary investigations, consider how score normalization could be implemented into the runtime speech recognizer and the literacy tutor application.
For step one, we would improve our analysis tools for word scores to plot the distributions of word scores. From this we could measure the degree of non-normalization present in the raw words scores, and evaluate the improvement resulting from any normalization method to be implemented.

Step two was to consider the factors that may be influencing the word score distributions that make them non-normalized. This analysis was to develop an intuition into what would be important in a method to normalize the scores.

The third step required coming up with a normalization method. Step four was the implementation of this method, which was tested in step five. In step six we determined how useful the normalization method is for the literacy tutor application.

It is perhaps worthwhile to mention what the ideal word score distribution would look like.

First of all, all scores for a word matched with a region of input where that word was actually spoken should be higher than all scores for that word matched with a region where that word was not spoken. Thus we have two separate sub-distributions of word scores for a word, one where the word was spoken and one where the word was not. These sub-distributions should be cleanly separated by a word acceptance (or rejection) threshold, so that the word score can be used to see if the word was correctly matched.

Within the sub-distributions, the scores should correspond to the quality of the pronunciation of the word for the correct matches, and some pronunciation similarity for the incorrect matches.

3.3 Phoneme Error Modelling

This method was not outlined in the original proposal, but we believed that it would prove useful in our efforts to provide feedback as to which sounds within a word are poorly pronounced. The above-mentioned methods inherently do not have any way of providing information at the sub-word level. Therefore, if we were to provide sub-word level feedback regarding mispronunciations, then we would need a method to do so. In general, this method called for experimenting with the phoneme representation of words in the phonetic dictionary used by the recognizer. By specifying potential phoneme level errors in the entries of the phonetic dictionary, the speech recognition system would have an opportunity to select a sequence of phonemes which more accurately represents the mispronounced word.

The Phonetic Decoder software requires two main knowledge sources: the phonetic dictionary and the syntax (or grammar). By considering the types of phonetic errors that occur ("miscue analysis") we planned to be able to provide a model of these errors to the recognizer via the phonetic dictionary. Theoretically, this would be done for each word to be used in the reading application. However, we anticipated that there would be a way to more globally indicate the range of potential phonetic errors to the recognizer without having to consider the specific errors for each word to be recognized. This could be done by considering the phonotactic rules of English which constrain the occurrences of phonemes in context. A meta-word could be designed which adequately models these constraints, and would thus provide a way of modelling phonetic errors which can be used for all words under consideration. For example, at a rather course level a meta-word to represent many one-syllable words could be constructed as [(C)(G)V(G)(C)], where C=consonant, G=glide and V=vowel. Parentheses indicate optional phonetic entities. A more complex meta-word to model one syllable words of English could be
3.3.1 Activities

1) Examine the phonetic errors made in reading tasks (i.e. miscue analysis).
2) Design a test.
3) Create phonetic error models for specific words.
4) Create meta-words to model phonetic errors.
5) Test utility of specific word phonetic error models vs. meta-word phonetic models.
6) Depending on results of preliminary tests, consider how phoneme modelling can be implemented into the runtime recognition system and literacy tutor application.

4. Results

In order to develop our speech recognizer to be able to detect speech which is pronounced incorrectly, we performed research in three areas: 1) syntactic error modelling; 2) score normalization; and 3) phoneme error modelling. Due to the success of these results, the acceptance/rejection techniques, along with score normalization, have been incorporated into the runtime speech recognition software. A sample demonstration application shows how these mechanisms can be utilized in an oral reading activity using speech recognition. The metaword syntax (and supporting phonetic dictionary) will also provide a way to get phoneme-level information about the spoken speech. However, it appears the accuracy of this output will only be functional for one-syllable words.

4.1 Syntactic Error Modelling Results

4.1.1 Preliminary Testing

A baseline test case for syntactic error modelling was completed, validating that this method can provide acceptable results. This test case was put together to give a quick idea of the feasibility of this method. First, a test case for isolated word recognition was chosen. We chose the first lesson from the Sight Words 2 Workbook, the second booklet in a series from the TV Tutor®. The reading lessons from this series are all isolated word reading tests of “sight” words. These are words that occur frequently in written English and that efficient readers recognize easily. Each lesson contains six words for students to read aloud, spell, etc. There are ten lessons for a total of 60 words in the workbook.

In this testing scenario, when each of the six words from Lesson 1 is being tested for accuracy, the remaining five words from Lesson 1 serve as the miscue words. The five miscue words and the remaining 54 words from the workbook serve as the non-test words which are listed in a syntax for recognition.

The test words from Lesson 1 are: round, must, under, any, pretty and open. We want to know not only the accuracy rates for each of these words, but also the correct rejection or false alarm rates. (In this scenario, each incorrect rejection is a false alarm.) Correct rejection rates tell us how often a non-test word is successfully recognized as any non-test word. False alarm rates (100% – CorRej%) indicate how often the miscue word is incorrectly recognized as the test word.
To generate test data we collected 10 repetitions of each of the six words in Lesson 1. This test data set was collected by each of three male adult speakers, giving us a total of 180 test tokens. These tokens are used in 6 different test situations to examine the performance of each as the "expected response" word. The recognition speaker model used to collect the data is the R3.4 Generic Male model, 3013.

4.1.2 Test Syntaxes

Six test syntaxes have been created to test how each of the six words performed with the recognizer. As mentioned above, when one of the six words is the test word, the other 59 words from the workbook serve as the potential observed responses in the syntax. Below is the syntax to use when round is the test word.

\[
S \rightarrow \{ \text{TESTWORD} \mid \text{POTENTIAL\_OBSERVED} \}
\]

\[
\text{TESTWORD} \rightarrow \text{round}
\]

\[
\text{POTENTIAL\_OBSERVED} \rightarrow \text{must} \mid \text{under} \mid \text{any} \mid \text{pretty} \mid \text{open} \mid \text{today} \mid \text{been} \mid \text{goes} \mid \text{night} \mid \text{walk} \mid \text{soon} \mid \text{boy} \mid \text{there} \mid \text{call} \mid \text{may} \mid \text{find} \mid \text{look} \mid \text{these} \mid \text{give} \mid \text{which} \mid \text{read} \mid \text{school} \mid \text{want} \mid \text{why} \mid \text{keep} \mid \text{milk} \mid \text{does} \mid \text{bird} \mid \text{ready} \mid \text{take} \mid \text{back} \mid \text{use} \mid \text{book} \mid \text{four} \mid \text{those} \mid \text{don't} \mid \text{birthday} \mid \text{laugh} \mid \text{friend}
\]
The test syntaxes for each of the other words is made by replacing round with the new test word. At the same time, round is placed into the POTENTIAL_OBSERVED category, and the new test word is removed from the POTENTIAL_OBSERVED list.

4.1.3 Preliminary Test Results

Tests for each of the six words were run initially on one speaker with the following results:

<table>
<thead>
<tr>
<th>Test Word</th>
<th>Accuracy</th>
<th>CorRejectPO</th>
</tr>
</thead>
<tbody>
<tr>
<td>any</td>
<td>40%</td>
<td>96%</td>
</tr>
<tr>
<td>must</td>
<td>70%</td>
<td>100%</td>
</tr>
<tr>
<td>open</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>pretty</td>
<td>50%</td>
<td>100%</td>
</tr>
<tr>
<td>round</td>
<td>40%</td>
<td>100%</td>
</tr>
<tr>
<td>under</td>
<td>80%</td>
<td>100%</td>
</tr>
</tbody>
</table>

Table 1 - Initial test with speaker LSO.

"Accuracy" is the recognition accuracy of the test word. "CorRejectPO" is the correct rejection rate of the five other words serving as miscue words. After observing these results, some minor changes were made to the syntaxes to remove POTENTIAL_OBSERVED words which were too often confused as test words. These words were:

any (except in the syntax for the test word any)
ate
today
take
every
night
bird
ready
don't
own
In addition, one change was made to the phonetic spelling of *round* in the recognition dictionary (by adding the [ə] vowel as an option to [a] in the [aʊ] diphthong). These minor changes improved accuracy for the test words while keeping the rejection rates to an acceptable level when tested with speaker LSO. Several more words were removed from the syntaxes to improve accuracy for two more speakers. These words were:

always
answer
please

The results of all three speakers using the final revised version of the syntaxes are displayed in Tables 2, 3 and 4. In addition to tests of correct rejection of words in the POTENTIAL_OBSERVED list, we also tested the correct rejection of words not in the syntax. These were six words taken from Lesson 10 of the *Sight Words 1 Workbook*: *again, would, very, or, many and only*. Each speaker donated five repetitions of each of the six words for this test. The rates of correct rejection for these words are in the "CorRejNonPO" column.

<table>
<thead>
<tr>
<th>Test Word</th>
<th>Accuracy</th>
<th>CorRejectPO</th>
<th>CorRejNonPO</th>
</tr>
</thead>
<tbody>
<tr>
<td>any</td>
<td>90%</td>
<td>94%</td>
<td>83%</td>
</tr>
<tr>
<td>must</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>open</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>pretty</td>
<td>90%</td>
<td>94%</td>
<td>87%</td>
</tr>
<tr>
<td>round</td>
<td>90%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>under</td>
<td>100%</td>
<td>98%</td>
<td>97%</td>
</tr>
</tbody>
</table>

Table 2 - Revised test with speaker LSO.

<table>
<thead>
<tr>
<th>Test Word</th>
<th>Accuracy</th>
<th>CorRejectPO</th>
<th>CorRejNonPO</th>
</tr>
</thead>
<tbody>
<tr>
<td>any</td>
<td>90%</td>
<td>100%</td>
<td>90%</td>
</tr>
<tr>
<td>must</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>open</td>
<td>90%</td>
<td>100%</td>
<td>90%</td>
</tr>
<tr>
<td>pretty</td>
<td>80%</td>
<td>100%</td>
<td>90%</td>
</tr>
<tr>
<td>round</td>
<td>100%</td>
<td>98%</td>
<td>93%</td>
</tr>
<tr>
<td>under</td>
<td>100%</td>
<td>98%</td>
<td>100%</td>
</tr>
</tbody>
</table>

Table 3 - Revised test with speaker BMD.

<table>
<thead>
<tr>
<th>Test Word</th>
<th>Accuracy</th>
<th>CorRejectPO</th>
<th>CorRejNonPO</th>
</tr>
</thead>
<tbody>
<tr>
<td>any</td>
<td>100%</td>
<td>100%</td>
<td>80%</td>
</tr>
<tr>
<td>must</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>open</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>
These results indicate that the recognition system has the ability to accurately recognize a word when pronounced correctly. It is also able to fairly reliably reject a set of miscue words when the expected response is the test word.

### 4.2 Acceptance/Rejection of Speech using Cheater Mode

Although the preliminary tests performed using syntactic error modelling for acceptance/rejection showed promise, we felt that we could not always rely on this syntactic component to perform adequately. We expected that it would be too difficult to develop an optimal syntactic model for every word spoken into the recognition system. And even though the syntactic error modelling method performed well for isolated word utterances, extending this method for use with multi-word utterances seemed particularly problematic.

Therefore, we determined that we could develop more confidence in the scores output by the decoder if the only parse being considered was the expected response. When the decoder prepares to provide text output, we would tell it beforehand only the exact words that are expected to be spoken. No other alternative parses are provided. When the decoder has only one parse for decoding, and that parse is the expected response, we term this *cheater mode*.

It was also necessary to develop a procedure to be able to easily interpret how the recognition system will behave with respect to correct acceptances, correct rejections, false alarms and incorrect rejections. A plotting scheme was designed in order to see how what percentage of the data would fall into each category. The main distinction between the data sets is scores from correctly pronounced words versus scores from incorrectly pronounced words.

Initially, we performed a comparison of the syntactic error modelling method versus the cheater mode method. We wanted to establish that cheater mode decoding would provide us with acceptable accuracy in terms of acceptance and rejection. Figure 1 shows a plot of the results of the three cases above ("TESTWORD", "Miscue in POTENTIAL_OBSERVED" and "Miscue NOT in POTENTIAL_OBSERVED"), but this time tested using cheater mode with the decoder. This plot is for the test word "any" for only one speaker, LSO. The vertical scale is the percentage of the data set. The horizontal scale is the range of utterance scores. The black squares indicate the percentage of the correctly pronounced utterances which would be rejected at a given score. The white squares and black diamonds mark the percentage of incorrectly pronounced utterances (miscues) which would be accepted at a given score. The cross point of these data sets indicates the optimal acceptance/rejection threshold. In other words, this point marks where the score is which will accept the most correctly pronounced utterances while rejecting as many incorrectly pronounced utterances as possible.

The cross point(s) on figure 1 can be compared with the results shown in the first line of table 2 above. For example, an utterance threshold value of '49' as shown in figure 1 would yield about 90% correct rejection of potential-observed words, while correctly accepting 100% of the test words. Table 2 has 94% and 90% for these values respectively.
Figure 1: Acceptance/Rejection Chart for "any" (LSQ)
Figure 2: Acceptance/Rejection Chart for "any" (LSO)
It is also possible to examine the acceptance/rejection threshold as it pertains to the scores assigned to individual words within an utterance. In the preliminary test case, all utterances contained only one word. Therefore, an acceptance/rejection plot of the word scores should be nearly identical in form to the plot for utterance scores. Figure 2 shows that this is the case (at least for this limited data set).

Since the preliminary isolated word test only chose miscue words at random, we needed to perform a more realistic test. We wanted a set of expected response data which had a corresponding set of realistic miscues. We attempted to locate both an isolated word test set and a multi-word test set, each of which had miscues which had been culled from actual reading tests or instruction.

For the isolated word test, we were unable to find any published results of actual miscues encountered with readers (at any grade level). We did locate several examples of lists of isolated words to be used in reading testing or for reading exercise, but none had provided a corresponding list of known miscues. Therefore, we created our own test set of approximately 300 words. A third of the words were the expected response words. Another third were the corresponding 'close' miscue; the final third were a 'less close' set of corresponding miscues. The 'close' miscues were chosen by their relative proximity to the expected response in two categories: grapho-phonemic similarity and semantic similarity. In the isolated word case we also were making the assumption that all miscues would be considered 'word substitutions'. (For example, there were no two-word miscues for an isolated-word expected response.) The words for this test are displayed in Appendix A. Speech data for this test set was collected from six male speakers.

For multi-word testing, we located case examples of reading miscues as explained in published literature. These reading miscues were mostly from stories read by elementary school children. (No case examples of adult reading miscues were discovered in the literature.) From these case examples, we compiled a set of 67 multi-word expected response sentences. Many (but not all) sentences had one or more corresponding miscue sentences. There were a total of 67 miscue sentences. Speech data for this set of 134 sentences was collected from five male speakers to comprise the multi-word test set. The sentences for this test set are given in Appendix B.

Figure 3 shows a chart of the two data sets for the new isolated word tests. The score scale is for utterance level scores. Figure 4 displays the results for the same test set, but using word level scores. The cross points indicate that an utterance (or word) threshold near 50 would result in about 25% of the correctly pronounced being rejected, while allowing 25% of the incorrectly pronounced words to be accepted. We expect that score normalization will improve this acceptance/rejection rate.

Figure 5 shows a chart of the results for the multi-word sentences. This plots word score information for three distinct data sets: 1) black squares indicate the percentage of correctly pronounced words in the correctly pronounced sentences which would be rejected at a given score; 2) white squares indicate the percentage of incorrectly spoken words in the miscue sentences which would be accepted at a particular score; and 3) black diamonds mark the percentage of correctly spoken words in the miscue sentences which would be rejected at a given score. In this case, a word threshold near '37' correctly accepts about 78% of the correctly spoken words, while correctly rejecting 78% of the mispronounced words.
Figure 3: Acceptance/Rejection Chart for Isolated Words

- %std340_chest_100
- %std340_miscue_100AB

Utterance Level Scores
4.3 Score Normalization

In order to gain some improvement in the acceptance/rejection thresholds, we implemented score normalization techniques in the decoder. In addition, we performed tuning of the score normalization mechanisms in the codebook in an attempt to improve the scores after they had been normalized.

4.3.1 Results of Score Normalization

We were able to perform the score normalization effort as described above in order to produce word and utterance scores which would be normalized to a score of zero. A test was performed to compare the scores produced by the decoder in "cheater mode" before normalization, and then after normalization. Figures 4 and 5 show the acceptance/rejection plots of word level statistics for the isolated-word and multi-word test before normalization; figures 6 and 7 show the same tests after normalization has been implemented in the decoding algorithms. The main effect here is a leftward shift in the optimal acceptance/rejection threshold to the region around '0' in the horizontal axes. This indicates that the normalization techniques are successful.

4.3.2 Results of Score Normalization Tuning

The expected phonetic code scores are used as the initial values for doing score normalization. The expected scores associated with the phonetic codes were determined from populations of the training data. This is the source of the initial scores of the phonetic codebook also.

A process of adjusting the scores of the codebook for improved accuracy is used to further prepare the codebook for delivery. An analogous method of adjusting the normalization scores for phonetic codes has been implemented to improve the normalization performance. The adjustment is accomplished by making slight modifications to the normalization scores and the codebook scores whenever they produce the wrong result, i.e., whenever the score of an incorrect decoding is higher than the normalization score, or when the score of a correct decoding is lower than the normalization score. If the normalization score classified the decoded result correctly, no adjustment is made.

We have called this method codebook tuning when applied to the codebook alone, and normalization tuning when applied to the codebook and the normalization scores together. The method used employs the Perceptron learning algorithm. The normalization tuning method extends the codebook tuning approach by using a threshold which is determined from the sum of the phonetic code specific thresholds (the normalization score offset values). This has the effect of training the normalization scores together with the codebook scores, so they should improve together.

Figures 8 and 9 show the acceptance/rejection results after normalization tuning has been applied to the phonetic codebook. Figure 8 contains the results of the isolated word test; figure 9 shows the results when tested using multi-word sentences. The figures show that the word scores are better normalized in that the acceptance/rejection cross point is located at zero on the horizontal (score) axes. The cross points also appear to be slightly lower on the vertical axis (than in non-normalized tests), indicating an improvement in the acceptance/rejection threshold. One other aspect of the normalized codebook is that it tends to cause more bad parses. This results in better rejection of mispronounced sentences. In
Figure 7: Acceptance/Rejection Chart for Multi-word Utterances vs. Normalized Word Level Scores
Figure 10: Acceptance/Rejection Chart for Isolated Words

Normalization Tuning Utterance Level Scores
figure 8 this can be observed in the upper left corner of the chart. The upward jump at the
left-most data point represents the percentage of mispronounced words which resulted in
bad parse rejections. In this test, these bad parses constitute nearly 30% of the
mispronounced data.

In the isolated word case, it seems that the utterance score can be used to achieve a better
acceptance/rejection threshold. This can be seen in figure 10 when compared with figure 8.
In figure 10, the cross point appears lower and the area is smaller in the triangle-shape
under the cross point.

4.4 Phoneme Error Modelling

We experimented with the creation of a meta word representation which could be useful in
determining the phonetic level errors which are made in pronunciation. We designed a
scheme of phonotactic constraints which would be present in all one-syllable words of the
English language. The basic scheme can be described as follows: the presence of at least
one vowel, which is optionally preceded and/or followed by one or a sequence of
(phonotactically legal) consonants. This can be displayed by the following set of
expansion rules:

\[
1\text{-Syllable} = \begin{cases} 
  (G_i | C_i | K_i) \\
  (V_o (K_f) | V_y G_y (K_y) | V_{wy} (G_w (K_w) | G_y (K_y))) 
\end{cases}
\]

where:

- \(G_i\) = word initial glides
- \(C_i\) = word initial single consonants
- \(K_i\) = word initial consonant clusters (i.e. any legal
  combination of glides and consonants)
- \(V_{wy}\) = "low back A" vowel (which precedes /y/ and /w/ in the
diphthongs of "buy" and "cow" respectively)
- \(V_y\) = "open O" vowel (which precedes /y/ in the diphthong of
  "boy")
- \(V_o\) = all other vowels (except "open O" and "low back A")
- \(G_y\) = the /y/ glide (which is word-final in "boy" and "buy")
- \(G_w\) = the /w/ glide (which is word-final in "cow")
- \(K_f\) = final single consonants except /y/ and /w/, and
  consonant clusters which do not begin with /y/ or /w/
- \(K_y\) = the consonant clusters which can follow the /y/ glide
- \(K_W\) = the consonant clusters which can follow the /w/ glide

() = contents are optional
{} = contents are and "either/or" choice
\(\|\) = choice separator

It was desirable to make some distinction for the /y/ and /w/ glides so that they would
combine appropriately with the "open O" vowel and the "low back A" vowel. Note that in
the designing of this scheme, we only considered the phonotactic constraints that occur in
the Western American dialect of English. This is due to the fact that our phonetic
transcription representation does hold to some particulars in symbology which are
consistent with this dialect. Some phonotactic combinations not allowed here might be considered appropriate for a representation of other (American) English dialects.

Once this scheme was designed, we attempted to implement it into the ASCII graph notation of our phonetic dictionary. This required the creation of a structure for a single dictionary entry which contained multiple phonetic representations. However, the tool to compile the ASCII representation into a binary file was unable to handle the size of the resulting dictionary graph. Therefore, we decided that we could implement the same phonotactic rule scheme outside of the dictionary by using the syntax phrase rule technique. Each phonetic element of the phonetic dictionary transcription set would need to be represented in the phonetic dictionary as a unique word. These "words" were then used to construct the phonotactically correct one-syllable meta-word via syntax phrase rules.

This one-syllable meta-words syntax was extended to account for multi-syllable words (and phrases) by allowing the syntax to be iterative with respect to the meta-syllable. We also wanted to test this metaword syntax to see how well it covered the English language. We were able to do this by creating a program which converts words to phoneme-words using a phonetic dictionary. We tested words and sentences of English, for a total of 3611 unique vocabulary items. As a result of this test, several changes were made to the metaword syntax to allow a more complete coverage of the phonotactics of English words. We were also forced to create some non-legal phonotactic rules in order to allow for some oddities in the phonetic spellings contained in our phonetic dictionary.

The resulting phrase rule structure for the metaword syntax is as follows:

\[
S \rightarrow \text{INIT\_SYLLABLE\_ (\{* \text{NEXT\_SYLLABLE\_ \}*\) )}
\]

\[
\text{INIT\_SYLLABLE\_} \rightarrow \{ \text{Gi | Ci | Ki} \} \\
| \text{Vo (Kf)} \\
| \text{Vy { Gy(Ky) | R\_ALL } } \\
| \text{Vwy { Gw(Kw) | Gy(Ky) } } \\
\]

\[
\text{NEXT\_SYLLABLE\_} \rightarrow \{ q_\} \{ \text{Gi | Ci | Ki | FLAP\_} \} \\
| \text{Vo (Kf)} \\
| \text{Vy { Gy(Ky) | R\_ALL } } \\
| \text{Vwy { Gw(Kw) | Gy(Ky) } } \\
\]

Vo == anoth aacute aquote aschwa enoth eacute eschwa iaacute inoth onoth oacute unoth uacute

Vy == ograve

Vwy == agrave

Ci == dh_ f_ h_ j_ s_ sh_ th_ v_ z_ zh_ m_ n_
    cx_ kx_ px_ tx_ bx_ dx_ gx_ jx_ q_

Gi == l_ r_ w_ y_

Gw == w_

Gy == y_

FLAP\_ == tt_
Ki -> {
  ((s_)\text{bx}_|f_\text{px}_\{l_\text{r}_|y_\}
  |(dx_\text{tx}_\{r_\text{w}_|y_\}
  |((s_)\text{gx}_|kx)_\{l_\text{r}_|w_\text{y}_\}
  |h_\{w_\text{y}_\}
  |th_\{r_\text{w}_\}
  |s_\text{dx}_\{r_\text{w}_\}
  |((l_\{s_\text{m}_|n_\{s_\text{l}_v_\}y_\)
  |(cx_\text{sh}_\{r_\}
  |s_\{f_\{l_\text{m}_|n_\text{w}_|bx_\text{dx}_|gx_\}

Ky -> {
  jx_\{dx_\}
  |dx_\{z_\}
  |s_\{tx_\{s_\}
  |z_\{dx_\}
  |((bx_\{m}_|v_\{dx_\{z_\}
  |n_\{((tx_\{th}_\{s_\})\{dx_\{z_\}
  |dh_\{dx_\{z_\}
  |l_\{((dx_\{z}_\{z_\}
  |\{px_\{kx}_|f_\{\{s_\text{t}_x_\}
  |tx_\{s_\}
  |r_\{z_\text{d}_x_\}

Kw ->
  jx_\{dx_\}
  |dx_\{z_\}
  |s_\{tx_\{s_\}
  |z_\{dx_\}
  |cx_\{tx_\}
  |dh_\{dx_\{z_\}
  |l_\{((dx_\{z}_\{z_\}
  |n_\{((tx_\{s_\}tx_\{s_\})\{dx_\{z_\}
  |th_\{((s_\text{t}_x_\}
  |tx_\{s_\}
  |r_\{z_\text{d}_x_\}

Kf -> \{ K\_LRf | K\_STOPf | K\_FRICf \}

K\_LRf -> \{ LONLY_ | RONLY_ | LRBO_TH_ \}

LONLY_ -> l_\{tx_\text{s_}_\text{tx}_\{f_\{\{s_\text{th}_\{s_\})\}\}

RONLY_ -> r_\{RONLY\_CLUSTERS\}

RONLY\_CLUSTERS -> \{n_\text{tx}_
  (s_\{l_\{((dx_\{z}_\{z_\})\{dx_\{z}_\})\}dh_\{dx_\{z}_\}\text{g}_\{dx_\{z}_\})\}

LRBOTH_ -> \{l_\{r_\} LRBOTH\_CLUSTERS

LRBOTH\_CLUSTERS -> \{(jx_\{dx_\\}dx_\{z_\}\{\text{n_} \{\text{d}_x_\{z}_\\{\text{z}_\}
  |s_\{tx_\{s_\})\}
  |\{bx_\{m}_|v_\{dx_\{z}_\})\text{c}_x_\{tx_\\}\{px_\{kx}_\{th}_\{s_\text{t}_x_\}
  |\text{sh}_\{tx_\\}tx_\{s_\})\text{z}_\}

25
The phoneme "words" as named above correspond to the SSI phonetic transcription representation as follows:

Anoth = /A/
Aacute = /A'/
Aquotes = /A"/
aschwa = /a/
Enoth = /E/
Eacute = /E'/
eschwa = /e/
Iacute = /I'/
Inoth = /I/
Onoth = /O/
Oacute = /O'/
Unoth = /U/
Uacute = /U'/
Ograve = /O"/
Agrave = /A"/
dh_ = /d/!
f_ = /f/
h_ = /h/
s_ = /s/
sh_ = /s/!
th_ = /t/!
v_ = /v/
z_ = /z/
zh_ = /zh/
m_ = /m/
n_ = /n/
ng_ = /ng/
The above phrase rule syntax is able to accept/generate sequences of phonemes which are phonotactically correct for a one-syllable word in English. Below are a few examples. If the phonemic representation corresponds to an actual English word, then the orthography (i.e. spelling) of that word is shown. Otherwise, a hypothetical orthography is shown.

joy: \texttt{jx\_ Ograve y\_}
guy: \texttt{gx\_ Agrave y\_}
myah: \texttt{m\_ y\_ Aacute}
prove: \texttt{px\_ r\_ Uacute v\_}
gyoip: \texttt{gx\_ y\_ Ograve y\_ px\_}
voyo: \texttt{v\_ y\_ Ograve y\_}
froit: \texttt{f\_ r\_ Ograve y\_ tx\_}
thrigh: \texttt{th\_ r\_ Agrave y\_}
pyow: \texttt{px\_ y\_ Agrave w\_}
chointh: \texttt{cx\_ Ograve y\_ n\_ th\_ s\_}

Although this generates phoneme sequences for real English words, it also generates sequences which are not "real" words. However, these words are considered "pronounceable" due to the phonotactic constraints which have been incorporated into the rules that generate them.

The metaword syntax can also generate/accept multiple-syllable words, as in these examples:

twizlyor: \texttt{tx\_ w\_ agrave y\_ z\_ l\_ y\_ Ograve r\_}
nyawilegg: \texttt{n\_ y\_ agrave w\_ Ograve y\_ l\_ eacute ng\_}
cielallyo: \texttt{kn\_ l\_ enoth l\_ q\_auction l\_ l\_ y\_ oacute}
orpya: \texttt{oggrave r\_ px\_ y\_ eschwa}
tragthrok: \texttt{cx\_ r\_ anoth gx\_ th\_ r\_ oacute kx\_}
nyoakdeng: \texttt{n\_ y\_ enoth kn\_ q\_ dx\_ w\_ eschwa ng\_}
broom-ain: \texttt{bx\_ r\_ agrave r\_ q\_ eacute n\_}
avbraw: \texttt{aggrave w\_ bx\_ r\_ agrave w\_}

We used a set of speech data from 4 male speakers who provided about 200 isolated words each. Results on one-syllable words appeared encouraging. However, phoneme accuracy dropped significantly when attempting to use the metaword syntax to decode multiple-syllable words. The phoneme accuracy for the multiple-syllable word test set was 53.13%; word recognition (i.e. getting all the phonemes correct for a given word) was only 3.97%.

We designed a method whereby we could tune the phonetic codebook to be better at decoding the phonemes. After six iterations of tuning, this resulted in some improvement, the best of which occurs with the fourth iteration (as shown below).
For the 4th iteration codebook, we examined the performance of several subsets of the data divided into groups by syllable counts. One-syllable words perform noticeably better.

<table>
<thead>
<tr>
<th>SYLLABLES</th>
<th>PHON ACC.</th>
<th>WORD ACC.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>65.02</td>
<td>17.14</td>
</tr>
<tr>
<td>2</td>
<td>60.09</td>
<td>2.53</td>
</tr>
<tr>
<td>3</td>
<td>56.28</td>
<td>0.53</td>
</tr>
</tbody>
</table>

We can improve performance only slightly by re-decoding each of these subsets of data using a different syntax. For the one-syllable words, we use a syntax that allows one and only one syllable. For the two-syllable words, we use a syntax that allows exactly two syllables, etc.

<table>
<thead>
<tr>
<th>SYLLABLES</th>
<th>PHON ACC.</th>
<th>WORD ACC.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>66.50</td>
<td>17.71</td>
</tr>
<tr>
<td>2</td>
<td>60.65</td>
<td>2.53</td>
</tr>
<tr>
<td>3</td>
<td>57.70</td>
<td>1.59</td>
</tr>
</tbody>
</table>

Even though these results may not seem very exciting, it may be that they are somewhat deceiving with respect to how well the recognizer is performing. When we examine the phoneme errors that are made, we see that many of the errors are close substitution errors. For example, the word pole is converted into phoneme-words as px{oacute} l_. The recognizer provides the following output for this word: bx{oacute} l_. This is actually very accurate, even though the "phoneme accuracy" is only 66%. If we interpret each phoneme into a set of distinctive features, a numerically calculated accuracy of bx{oacute} l_ would be much higher. Even if we consider an extremely simple "3-feature" representation of each phoneme such as place, manner and voicing, we can see that getting bx{oacute} l_ for the word pole would be 88% accurate rather than 66%. This type of consideration would also be feasible for the literacy tutor application since a mechanism may need to be developed to provide "friendly" feedback, instead of simple phonetic feedback which may be uninterpretable by students. (e.g. A student may make better progress by receiving the feedback "Say it again, this time popping the 'p' more", rather than "Say it again, this time more like 'p' than 'b'.")

4.5 Demonstration Software

In the spring of 1991, we supplied a preliminary version of the demonstration software to the staff at NASA Johnson Space Center who are working on the Literacy Tutor project. We consulted with them on how they could integrate this speech recognition application into a demonstration which would utilize the Macintosh to control the active recognition syntax. We then created an enhanced version of the speech application to also handle receiving information from a serial line (which would be connected to the Macintosh). The executable and source code for this sample program was shipped for them to prepare for their March 12th demonstration.
For the final deliverable, we have enhanced this application. It now allows a sentence to be sent in to the serial port. This sentence is the expected response. The application will use the new score normalization techniques and tuned codebook (norm.prf), along with the acceptance/rejection thresholds to notify when a word or sentence has been poorly spoken. For phoneme level feedback, we are delivering the metaword syntax and the speaker model (meta.prf) that has been tuned for use with the metaword grammar. The metaword could easily be incorporated into the demonstration application to do "second-pass" decoding or "re-prompting" of isolated words after they have been "rejected" by the acceptance/rejection threshold. The best phoneme output for that word could then be sent to a module to determine appropriate user feedback and pronunciation instruction. The application can use the codebook switching mechanisms in the Phonetic Decoder Interface to enhance performance for sequential decoding, using the normalized speaker model in the acceptance/rejection phase, and the metaword speaker model for decoding to the phoneme level.

5. Conclusion

The research performed for this project was successful in providing better mechanisms for using speech recognition in a literacy tutor application. Using a combination of scoring normalization techniques and cheater-mode decoding, we are able to provide a reasonable acceptance/rejection threshold. In continuous speech, the system has been tested to be able to provide above 80% correct acceptance of words, while correctly rejecting over 80% of incorrectly pronounced words.

Acknowledgements

Special thanks to the following employees at Speech Systems Incorporated for their support on this project: Mark Anikst, Robbie Ishihara, Olivia Pangerapan and John Turley.
## Appendix A: Isolated-Word Test Sentences

Note: The expected response is in the first column. The corresponding 'close' miscue is in the second column, with the 'less close' miscue in the third column.

<table>
<thead>
<tr>
<th>ER:</th>
<th>Miscue A:</th>
<th>Miscue B:</th>
</tr>
</thead>
<tbody>
<tr>
<td>foreign</td>
<td>forward</td>
<td>for</td>
</tr>
<tr>
<td>midline</td>
<td>middle</td>
<td>outlined</td>
</tr>
<tr>
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<td>absence</td>
<td>branch</td>
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<tr>
<td>scattered</td>
<td>scarring</td>
<td>pattern</td>
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<td>curved</td>
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<td>dual</td>
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<td>structures</td>
<td>fracture</td>
</tr>
<tr>
<td>widespread</td>
<td>wide</td>
<td>withdrawal</td>
</tr>
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<td>early</td>
</tr>
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<td>largest</td>
<td>longer</td>
</tr>
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<td>rhonchi</td>
<td>margins</td>
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<td>if</td>
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<tr>
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<td>bulb</td>
</tr>
</tbody>
</table>
Appendix B: Multi-Word Test Sentences

Note: Expected response sentence are preceded by "ER:". Sentences that follow an ER sentence are miscue sentences for that expected response.

**ER:** joe was not happy

**ER:** he wanted a pet
  he's asked a pet

**ER:** he found a pet
  he for a pet

**ER:** it was a goat
  is was a

**ER:** mom said no

**ER:** dad said no no no

**ER:** no goat for joe
  no not for john

**ER:** joe heard a sound
  john was sad

**ER:** he looked around
  he looked he looked

**ER:** it was a dog-

**ER:** a little dog

**ER:** joe patted the dog
  john patted the dog

**ER:** hello joe said
  hello john said

**ER:** i like you

**ER:** bow-wow
  boo-hoo said the dog

**ER:** nice dog said joe
  dog said john

**ER:** come with me

**ER:** be my dog
  be my pet

ER: be my pet
at last uncle bill and harriet and mom and dad were at home
at last bill and hi and moo and dad we were at home
at last bill and hi hay her and moo and dad we were at home

harriet said i'll go to see my friends
harry said i'll go to see my friend

all of them have missed me so much
i'll all of them have made some me so much

i know they all will want to see me
i know that i'll what to see me

that's a very good idea said mom
that's a very good answer said moo

why don't you go see all of them

harriet ran to pat's house
hare are ride to pick home to pick's home
hare ride to pick home
hare are to pick home

she ran up to the door
she ride up to the door

put puts moo come to see her

is pat home asked harriet
its put home answered hare
its is it is put home answered hare

he will want to see me

i have been away

no said pat's mom
no said pat moo

pat is not here
pat said not here

he is away right now
he is away wry now right now

but he didn't say he missed you
but he didn't say he must you

i can get to the park fast
i can get ahead to the park first faster
i can get ahead to the park first
i can get ahead to the park faster
ER: you and i will run
you and i will race

ER: we will run to the park
we will race to the park

ER: i can run fast and you can't
i can run fast you can't

ER: turtle said you can run fast rabbit and i can't
turtle said you can run fast rabbit but i can't

ER: that's why i got here first
that's how i got here first

ER: you run fast rabbit
you can run fast rabbit
you are fast rabbit

ER: but you stop and i don't
but you stopped and i didn't

ER: you can't run turtle
i can't run turtle
you can run turtle
you can't run [fA"] turtle

ER: we will run to the park
i will run to the park

ER: i'll fix a light and drop it to you
i'll fix the light and drop it to you

ER: mrs. miller had gone to visit a neighbor
mrs. miller had gone to visit the neighbor

ER: it was safely outlined in a library book
it was safely outlined in the library book

ER: in one corner and along one side
in the corner and along one side
in one corner and along the side
in the corner and along the side

ER: he was hanging up the two telephones
he was hanging up two telephones
he was hanging up the telephones

ER: then one afternoon he left
then the afternoon he left

ER: one picture showed a large black crow
a picture showed a large black crow
ER: he printed them upstairs in his darkroom
he printed them upstairs in the darkroom

ER: after the cut in his allowance
after the cut in the allowance

ER: he hurried to his cellar work table
he hurried to the cellar work table

ER: it was in his toolbox
it was in the toolbox

ER: the lady led me toward his office
the lady led me toward the office

ER: she was playing with the camera
she was playing with her camera
she was playing with a camera

ER: he was always like one of the uncles
he was always like one of his uncles

ER: he was a real chemist with a company in switzerland
he was a real chemist with his company in switzerland

ER: she came to the house
she came to our house

ER: he wagged a finger at andrew
he wagged his finger at andrew

ER: he was grabbing for the finger
he was grabbing for his finger
he was grabbing for your finger
he was grabbing for a finger

ER: they were pictures of their father
they were pictures of the father

ER: they took pictures of their mother
they took pictures of the mother

ER: that's mine said my baby brother
that's mine said the baby brother
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