

TRANSCRIPTION OF BROADCAST TELEVISION AND RADIO NEWS: THE 1996 ABBOT SYSTEM

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ABSTRACT

This paper describes the development of the CU-CON system which participated in the 1996 ARPA Hub 4 Evaluations. The system is based on ABBOT, a hybrid connectionist-HMM large vocabulary continuous speech recognition system developed at the Cambridge University Engineering Department [4]. The Hub 4 Evaluation task involves the transcription of broadcast television and radio news programmes. This is an extremely demanding task for state-of-the-art speech recognition systems. Typical programmes include a wide variety of speaking styles and acoustic conditions. These range from read speech recorded in the studio to extemporaneous speech recorded over telephone channels.

1. INTRODUCTION

The hybrid connectionist-hidden Markov model approach uses an underlying hidden Markov process to model the time-varying nature of the speech signal and a connectionist system to estimate the observation likelihoods within the hidden Markov model (HMM) framework. ABBOT is a large-vocabulary speech recognition system based on the hybrid approach which utilises a recurrent network for acoustic modelling. The major advantage of this approach is that the recurrent network acts as a non-parametric model that is able to capture temporal acoustic context. Consequently, the basic ABBOT system is able to achieve very good performance using single pass decoding and context-independent phone models [6].

This paper reports on the development of the CU-CON system for the 1996 ARPA Evaluations. The 1996 Hub 4 Evaluation task is presented in the following section. This includes a description of the acoustic and language modelling data supplied to participating sites. Section 3 describes the acoustic models used for the 1996 evaluations, and the process of training a new set of models on the broadcast news acoustic training data. This includes a description of the linear input network (LIN) technique used for channel adaptation. This method has been used to adapt the acoustic models used for telephone speech, and for speech in degraded acoustical conditions. Section 4 outlines the procedure used for creating a lexicon and language model, plus a description of the training texts used, and the procedure for producing pronunciations. Next the performance of the system at various stages of development is assessed on the 1996 Hub 4 development test data. The final section presents the official results on the Hub 4 evaluation test data.

2. THE 1996 ARPA HUB 4 TASK

The 1996 evaluation consists of two components, a “partitioned evaluation” (PE) component, and an “unpartitioned evaluation” (UE) component. The PE contains speech that is manually segmented into homogeneous regions, and provides a set of six controlled contrastive conditions known as “evaluation focus conditions”:

F0: Baseline broadcast speech

This condition describes speech that is directed to the general broadcast audience, and is recorded in a quiet studio environment. The speech is assumed to be mostly read from prepared texts.

F1: Spontaneous broadcast speech

This condition describes speech that is directed to one or more human conversational partners, and is recorded in a quiet studio environment. The speech is assumed to be spontaneous/conversational.

F2: Speech over telephone channels

This condition describes speech that is recorded over reduced-bandwidth conditions, such as local or long distance telephony.

F3: Speech in the presence of background music

This condition describes speech that satisfies the conditions of baseline broadcast speech, or spontaneous broadcast speech, except that it is broadcast with additive background music.

F4: Speech under degraded acoustical conditions

This condition describes speech that is acoustically degraded for reasons other than the use of telephone channels or the presence of background music. Sources of degradation include additive or environmental noise.

F5: Speech from non-native speakers

This condition describes speech that satisfies the attributes of baseline broadcast speech, except that it is spoken by non-native speakers of American English. It is assumed to be spoken by fluent speakers of English with a foreign accent.

Segments that do not fall within the specification for the focus conditions presented above are labelled FX. The UE is similar to the 1995 Hub 4 evaluation in that it contains relatively complete portions of television and radio news broadcasts, but using a wider variety of source material than was employed in the 1995 evaluation. The CU-CON system participated in the PE only.

The acoustic training data provided to each of the participating sites consists of 50 hours of data from a selection of U.S. radio and television shows. Certain portions of these shows, including sports results and weather forecasts, are

not transcribed, and so the total amount of transcribed acoustic training data is approximately 35 hours. In addition to the transcriptions, NIST provided timing information for segmenting the data into the focus conditions. Table 1 shows the total amount of each data for each of the focus conditions.

Focus	Proportion	Time (hours)
F0	33.73%	11.94
F1	16.03%	5.67
F2	20.69%	7.32
F3	4.68%	1.66
F4	9.84%	3.48
F5	0.76%	0.27
FX	14.27%	5.05

Table 1. Amount of acoustic training data by focus condition.

The supplied language model training data is from the “Broadcast News” CDROMs produced by Primary Source Media, Inc. and covers the period from January 1992 to April 1996. This contains approximately 132 million words.

3. ACOUSTIC MODELS

This section describes the acoustic modelling process used in the ABBOT system. This includes a brief description of the front-end, the recurrent network, and phonetic context-dependent modelling which augments the standard context-independent model.

3.1. Acoustic Feature Representation

Two sets of acoustic features have been used in the past by the ABBOT system: MEL+, a 20 channel mel-scaled filter bank with energy, degree of voicing, and pitch [9], and PLP, 12th order cepstral coefficients derived using perceptual linear prediction and log energy [2]. The 1996 ABBOT system uses both MEL+ and PLP acoustic features. The MEL+ and PLP features were computed from 32 msec windows of the speech waveform every 16 msec. To increase the robustness of the system to environmental conditions, the statistics of each feature channel were normalised to zero mean with unit variance over each segment.

3.2. Acoustic Model Architecture

The acoustic model is a recurrent neural network which estimates posterior phone probabilities. These are converted to scaled likelihoods for use as observation probabilities within phone HMMs [10, 11].

Each of the acoustic models has been augmented with limited word-internal context-dependent modelling. By using the definition of conditional probability, the factorisation of conditional context-class probabilities is used to implement phonetic context-dependency in the acoustic model [5]. Single-layer networks or “modules” are used to estimate conditional context-class posteriors, and leads to a total of 604 context-dependent phone classes for this task.

The 1996 ABBOT system utilises recurrent networks trained on forward-in-time and backward-in-time input sequences of both the MEL+ and PLP feature vectors. The recurrent network builds up a representation of the past acoustic context which implies the ordering of the input data is important. A significant performance improvement is achieved by merging multiple recurrent networks trained on these different input representations [3].

3.3. Acoustic Model Training

This section describes the development of the acoustic models used in the 1996 ABBOT system.

A Viterbi forced alignment was performed using the 1995 ABBOT acoustic models. These are forward and backward in time PLP models trained on the secondary channel data from the Wall Street Journal corpus (SI84). Average log probability scores were generated for each segment. Those segments with poor scores were checked manually. It was found necessary to edit the transcriptions or time markings for approximately 2.5% of the segments.

A forward and backward PLP model was then trained on all of the broadcast news data. Forward and backward MEL+ models were also trained on this data. Only one Viterbi alignment was performed due to the late arrival of the acoustic training data, and the lack of time available. These models are denoted **BN**. A further 4 acoustic models were trained solely on the F0 segments. These comprise forward and backward in time models for both MEL+ and PLP, and are denoted **BN.F0**.

3.4. Channel Adaptation

The **BN** models were extended to the F2 and F4 conditions by means of linear input network (LIN) adaptation on the training data [7].

The F2 data was marked as either having low or medium fidelity. We reclassified all the F2 data into narrow or wide band data based on the power in the upper 4kHz of the spectrum. However, merely averaging the power in the upper 4kHz of a segment would bias the classification due to the relative number of voiced and unvoiced sections in a segment. To account for this we multiplied the energy in the upper 4kHz of each frame by the estimated probability of the frame representing an unvoiced segment. We chose a threshold for the choice of narrow bandwidth and full bandwidth by manually classifying a small proportion of the F2 segments. After setting the threshold all the F2 segments were relabelled. A LIN was trained for each **BN** model on the narrow bandwidth F2 data. These adapted models (denoted **BN.adpt-nb**) were used on the eval data classified as narrow bandwidth. Those segments classified as F2 wideband were recognised using the **BN** model set without adaptation.

For the F4 condition LIN networks were trained on those segments labelled as F4 in the training data. These models are denoted **BN.adpt-F4**.

4. LANGUAGE MODEL AND LEXICON

Two different language models were used, one for speech considered “planned”, and one for speech considered “spontaneous”. Table 4 shows the different text sources for the language model training data. The 1995 Hub 4 data covers general North American business news. The Marketplace data is the transcriptions of the training data supplied for the 1995 Hub 4 Evaluation. The transcriptions of the broadcast news acoustic training data were also used for training the language models.

The 1996 ABBOT system uses a 65,532 word vocabulary. This was produced by extracting the most frequent 80,000 words from the broadcast news text data only, and removing misspelled words, processing errors etc.

Trigram language models were built using an alpha release of the CMU-Cambridge Statistical Language Mod-

Texts	N ^o . Words	Language Model
Broadcast News	132 million	planned, spont.
1995 Hub 4 texts	108 million	spont.
1995 Marketplace	50,000	planned, spont.
1996 transcripts	380,000	planned, spont.

Table 2. LM training data.

elling Toolkit version 2.0.¹ The language models used by ABBOT for previous evaluations have used the Good-Turing discounting method. However, this year's language models have used the Witten-Bell discounting method [12].

The recognition lexicon includes priors on multiple pronunciations. The priors are normally calculated by gathering the statistics from a forced alignment. This year these multiple pronunciation priors have been reestimated (and smoothed with the statistics from the standard forced alignment), for spontaneous speech. The statistics were gathered from a forced alignment on a phone string recognition of the F1 and F2 training data.

5. RESULTS

Table 3 shows results on the development test data for various systems. These systems represent various stages in the development of the 1996 ABBOT system:

Focus	Word Error Rate %		
	System 1	System 2	System 3
F0	31.9	22.9	18.8
F1	58.0	46.8	40.9
F2	66.6	51.6	45.7
F3	62.9	46.6	40.7
F4	48.2	33.8	27.4
F5	44.7	36.6	31.5
FX	73.0	61.7	58.1
Overall	54.6	42.7	37.5

Table 3. Results on the development test set.

System 1: This is based on the 1995 ABBOT system, except that only a single forward context-independent PLP network was used. The acoustic model training data is the short term speakers from WSJ0 secondary channel (SI84). The standard ARPA 1995 60,000 word trigram language model was used.

System 2: This system uses forward and backward PLP broadcast news context-independent acoustic models. A trigram language model trained only on the broadcast news text is used. The system has a 65,532 word vocabulary.

System 3: This system uses word-internal context-dependent forward and backward PLP acoustic models. The same language model as **system 2** was used.

From the results it can be seen that using the broadcast news acoustic and language modelling training data, and merging forward and backward acoustic models has resulted in a significant reduction in error rates. The overall error rate has been reduced from 54.6% to 42.7%, a reduction of 22.8%. The addition of limited word internal context-dependent models has further reduced the overall word error rate to 37.5%, a improvement in performance of 12.2%. Note that the adapted models **BN.adpt-nb** or **BN.adpt-F4**

¹Details of the CMU-Cambridge Statistical Language Modelling Toolkit version 2.0 can be found at:
http://svr-www.eng.cam.ac.uk/~prc14/toolkit_documentation.html

have not been evaluated on the development data due to lack of time. The models trained only on those segments marked F0 (**BN.F0**) result in a word error rate of 16.2% on the F0 segments of the development test set, a reduction of 13.8% compared to the BN models.

6. EVALUATION SYSTEM

The CU-CON evaluation system used a number of features that were not used on any of the systems evaluated on the development data. Different language models were used for segments marked as planned speech and segments marked as spontaneous speech. In addition, channel adaptation was used for reduced bandwidth F2 segments, and for the F4 segments. Side information indicating planned or spontaneous speech is provided with the FX segments. This information was used to select the appropriate acoustic and language model to use for each of the FX segments. Table 4 lists the acoustic and language models used for each of the segments in the evaluation test data. Note that the narrow band, wide band classification of the F2 and FX-F2 segments was accomplished using the method described in Section 3.4.

Focus	Acoustic Model	Language Model
F0	BN.F0	planned
F1	BN	spont.
F2.nb	BN.adpt-nb	spont.
F2.wb	BN	spont.
F3	BN	planned
F4	BN.adpt-F4	planned
F5	BN	planned
FX-F1	BN	spont.
FX-F2.nb	BN.adpt-nb	spont.
FX-F2.wb	BN	spont.

Table 4. Acoustic and language models used for the various focus conditions.

Table 5 shows the official word error rates of the CU-CON system on the 1996 Hub 4 evaluation test data. The number of words per focus condition is also included. Single pass decoding was performed using the NOWAY decoder [8]. No test set adaptation was performed for this evaluation.

Focus	N ^o . Words	WER %
F0	5995	25.8
F1	6593	33.5
F2	1748	40.4
F3	1417	33.4
F4	1833	39.3
F5	299	40.5
FX	2301	53.1
Overall	20186	34.7

Table 5. Number of words and word error rate by focus for the CU-CON evaluation system.

Comparison with the results in Table 3 shows that error rates for the baseline F0 condition are significantly higher on the evaluation data. The perplexity of the F0 segments of the development and evaluation data is similar, as is the signal-to-noise ratio (SNR) (27.6dB for the evaluation data, and 29.4dB for the development data). It is therefore surmised that the F0 evaluation data contains more conversational type speech than it's development counterpart.

The perplexity for the different focus conditions is shown in Table 6. The F0 perplexity is considerably higher than seen

Focus	Perplexity	OOV Rate %
F0	205.28	1.59
F1	120.57	1.40
F2	150.22	1.63
F3	285.18	1.53
F4	128.20	0.59
F5	271.14	0.33
FX	167.29	0.96

Table 6. Perplexity and OOV by focus for the CU-CON evaluation system.

for read speech in previous evaluations. Typical perplexity values for the 1995 Hub 3 Evaluation test data were in the region of 130 for trigram language models.

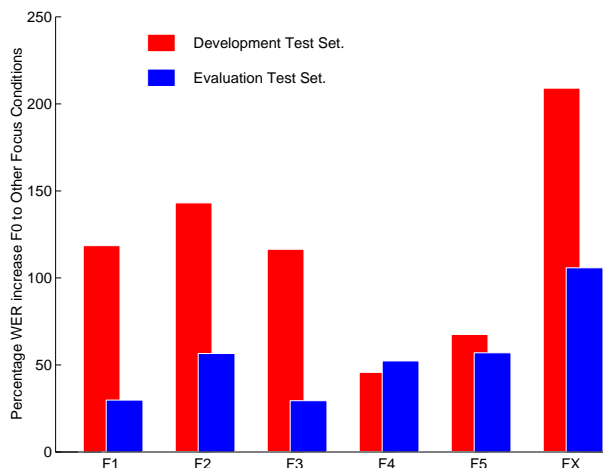


Figure 1. Relative WER increase from the baseline F0 focus condition to each of the other focus conditions.

Figure 1 shows the degradation in performance of the different focus conditions as measured against the baseline F0 focus, for both the development and evaluation test data. It can be seen that a far greater degradation was observed on the development data, however, this is likely to reflect the significantly lower word error rate of F0. The relative degradation between each of the focus conditions is similar for the development and evaluation data, except for the F4 and F5 focus conditions. These exhibit a far greater degradation on the evaluation data when compared with the other focuses. Investigation has revealed that the SNR of the F4 data is 25.1dB for the development data, but only 18.6dB for the evaluation data. This is likely to be the reason for the greater F4 degradation. The source of the extra degradation seen for the F5 focus condition is most probably due to the far higher perplexity seen in the evaluation data, which is 28% higher than on the development data.

7. CONCLUSIONS

This paper has described the development of the CU-CON system for the recognition of broadcast television and radio news. This has concentrated on building acoustic and language models on data from this domain. This approach was necessitated by the late arrival of the training data. Further work on this task is planned, and includes the use of boosting [1], extended context-dependent modelling, test set adaptation, and speech enhancement.

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