State-Transition Interpolation and MAP Adaptation for HMM-based Dysarthric Speech Recognition

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Abstract

This paper describes the results of our experiments in building speaker-adaptive recognizers for talkers with spastic dysarthria. We study two modifications – (a) MAP adaptation of speaker-independent systems trained on normal speech and, (b) using a transition probability matrix that is a linear interpolation between fully ergodic and (exclusively) left-to-right structures, for both speaker-dependent and speaker-adapted systems. The experiments indicate that (1) for speaker-dependent systems, left-to-right HMMs have lower word error rate than transition-interpolated HMMs, (2) adapting all parameters other than transition probabilities results in the highest recognition accuracy compared to adapting any subset of these parameters or adapting all parameters including transition probabilities, (3) performing both transition-interpolation and adaptation gives higher word error rate than performing adaptation alone and, (4) dysarthria severity is not a sufficient indicator of the relative performance of speaker-dependent and speaker-adapted systems.

1 Introduction

After more than two decades of research, speech recognition is a well-established and reliable human-computer interaction technology. The accuracy of the newest generation of large vocabulary speech recognizers, after adaptation to a user without speech pathology, is high enough to provide a useful human-computer interface especially for people who find it difficult to type with a keyboard.

Automatic speech recognition (ASR) systems generally assume that the speech signal is a realisation of some message encoded as a sequence of one or more symbols. To effect the reverse operation of recognising the underlying symbol sequence given a spoken utterance, the continuous speech waveform is first converted to a sequence of equally spaced discrete parameter vectors. The role of the recogniser is to effect a mapping between sequences of speech vectors and the wanted underlying symbol sequences. Most speech recognizers today are based on the hidden Markov model (HMM) paradigm: it is assumed that the sequence of observed speech vectors is generated by a Markov model as shown in Fig. 1. A Markov model is a finite state machine which changes state once every time unit and each time $t$ that a state $j$ is entered, a speech vector $o_t$ is generated from the probability density $b_j(o_t)$ which

![Figure 1: The Markov generation model.](image-url)
is a mixture-Gaussian density for most standard systems. The transition from state $i$ to state $j$ is also probabilistic and is governed by the discrete probability $a_{ij}$. Fig. 1 shows an example of this process where the five state model moves through the state sequence $X = 1, 2, 2, 3, 4, 4, 4, 5$ in order to generate the sequence $o_1$ to $o_7$. The entry and exit states $(1, 5)$ are non-emitting. This is to facilitate the construction of composite models: most systems use HMMs to perform modeling at the phone-level rather than word-level; as such, word-level models are constructed by stringing together phone-level HMMs for the constituent phones.

Fig. 2 shows how HMMs can be used for isolated word recognition. Firstly, an HMM is trained for each vocabulary word using a number of examples of that word – given a set of training examples corresponding to a particular model, the parameters of that model ($\{a_{ij}\}$ and $\{b_j(o_t)\}$) are determined by a robust and efficient re-estimation procedure. In this example, the vocabulary consists of just three words: “one”, “two” and “three”. Secondly, to recognise some unknown word, the likelihood (probability) of each model generating that word is calculated and the most likely model identifies the word.

For creating a speech recognizer for a particular speaker, there are two approaches: one is to create a speaker-dependent (SD) system by utilizing speech of that speaker alone to train the HMMs; the other is to create a speaker-adapted (SA) system by first training the HMMs in a speaker-independent fashion by utilizing speech of several speakers, and then customising the HMMs to the characteristics of the particular speaker by using training examples of their speech to modify the HMM parameters. The parameter values do not get overwritten; they are adjusted using a regularized or constrained machine learning algorithm. Regularization (e.g., using Maximum A Posteriori learning) or constraints (e.g., using linear transformations) allow the SA model to use far more trainable parameters per minute of training data without over-training the system.

Despite the advances in speech technology, their benefits have not been available to people with gross motor impairments mainly because these impairments include a component of dysarthria – a group of motor speech disorders resulting from disturbed muscular control of the speech mechanism due to damage of the peripheral or central nervous system. Dysarthria is often a symptom of a gross motor disorder, whose other symptoms usually make it hard to use a keyboard and mouse. Published case studies have shown that some dysarthric users may find it easier to use an ASR system instead of a keyboard (Carlson and Bernstein, 1987; Coleman and Meyers, 1991; Deller et al., 1988; Deller et al., 1991; Fried-Oken, 1985). Polur and Miller studied the development of HMM-based small vocabulary (eight repetitions each of ten digits and fifteen ‘command’ words in English) SD systems for three male subjects subjectively classified by a trained clinician as moderately dysarthric (Polur and Miller, 2005a; Polur and Miller, 2005b). They found that an ergodic HMM with a slight left-to-right character (called a transition-interpolated HMM from hereon) provides higher word recognition accuracy (WRA) than a standard left-to-right HMM, apparently because the transition-interpolated HMM is able to capture outlier events as a backward or nonlinear progress through the intended word. The benefit of using ergodic modeling over left-to-right modeling in distorted speech applications with disruption events, pause events, and limited training data has also been noted earlier by Deller, Hsu and Ferror (Deller et al., 1991). Section 2.1.2 explains
in more detail the difference between these HMM topologies.

Speaking for long periods of time is tiring, especially for a person with dysarthria, therefore it is difficult for a person with dysarthria to train a speaker-dependent ASR. Speaker adaptation then seems a useful method to overcome this obstacle in developing dysarthric speech recognizers. Raghavendra et al. (Raghavendra et al., 2001) have compared recognition accuracies of an SA system and an SD system. They found that the SA system adapted well to the speech of talkers with mild or moderate dysarthria, but the recognition scores were lower than for an unimpaired speaker. The subject with severe dysarthria was able to achieve better performance with the SD system than with the SA system. These findings were also supported by Rudzicz (Rudzicz, 2007) who compared the performance of SD and “SA” systems on the Nemours database (Menendez-Pidal et al., 1996) by varying independently the amount of data for training and the number of Gaussian components used for modeling the output probability distributions. The “SA” technique implemented is not speaker-adaptation in the conventional sense: it uses the parameter values for the speaker-independent system as the starting point to train HMMs for a particular dysarthric speaker. In a training algorithm without regularization or constraint terms, it is possible for a system of this type to over-train, resulting in loss of accuracy on test data from the same speaker, and Rudzicz’s results suggest that such over-training may have occurred in some cases. He further concluded that there was not enough data in the database to represent intra-speaker variation.

The study described in this paper investigated the development of medium vocabulary HMM recognizers for dysarthric speech of various degrees of severity with the following aims: (1) to test the performance of SA systems relative to SD systems, for various degrees of dysarthria severity, (2) to test the performance of an SD system employing transition-interpolated HMMs relative to an SD system using strictly left-to-right HMMs, (3) to test the performance of an SA system with transition-interpolated HMMs relative to an SD system having strictly left-to-right HMMs and, (4) to see if the results in the above three cases are essentially a function of the talker’s dysarthria severity.

2 Experimental Setup

2.1 Modifications investigated

The following modifications to the HMM structure were studied in our experiments:

2.1.1 Adaptation

All SA systems were developed by adapting a speaker-independent system in a Maximum A Posteriori (MAP) manner, as outlined by Gauvain and Lee (Gauvain and Lee, 1991; Gauvain and Lee, 1992). MAP adaptation involves the use of prior knowledge about the model parameter distribution. Hence, if we know what the parameters of the model are likely to be (before observing any adaptation data) using the prior knowledge, we might well be able to make good use of the limited adaptation data, to obtain a decent MAP estimate. For MAP adaptation purposes, the informative priors that are generally used are the speaker independent model parameters (empirical Bayes approach). In (Gauvain and Lee, 1991), they derive expressions of MAP estimates for all HMM parameters except the transition probabilities (Gaussian mixture-component means, diagonal Gaussian mixture-component covariance matrices and, mixture-component weights) and also provide an initialization scheme for the prior density of these parameters. In (Gauvain and Lee, 1992), they derive expressions for MAP estimates of transition probabilities in addition to those for full-covariance Gaussian mixture-component parameters, and provide a MAP variant of the Expectation-Maximization (EM) re-estimation algorithm. All systems developed in our study modeled the observations as mixture of Gaussians with diagonal covariance matrices.

2.1.2 Transition-Interpolation

Fig. 3 illustrates the topologies of strictly left-to-right (LR) and transition-interpolated (TI) HMMs with 3 emitting states. If \( A = \{a_{ij}\} \) be the \( N \times N \) transition probability matrix for an N-state HMM, then we have for an LR HMM: for each state \( i \), \( 0 < a_{ii} , a_{i,i+1} < 1; a_{ii} + a_{i,i+1} = 1 \) and \( a_{ij} = 0 \) for \( j \neq i, i+1 \). In other words, each emitting state has only two possible state-transitions: given the current state, the HMM either remains in the
same state or moves into the succeeding state; it will not jump over states or go to a preceding state.

Figure 3: Difference between strictly left-to-right and transition-interpolated HMM topologies.

The TI model is an LR model which has non-zero transition probabilities for jumps and transitions to preceding states from a particular state (for emitting states). These probabilities are however small compared to self-transition and next-state–transition probabilities. A TI HMM is initialized as follows: for each emitting state $i$, $a_{ij} = \epsilon$ for $j \neq i, i+1$ where $0 < \epsilon << 1$; $a_{ii}$, $a_{i,i+1} >> \epsilon$ and $\sum_{j=1}^{N} a_{ij} = 1$. After this initialization, the transition probability matrix is re-estimated for speaker-dependent systems using the standard Maximum Likelihood EM algorithm, and for speaker-adapted systems using the MAP variant of the EM algorithm.

2.2 Data used

The experiments described in this paper utilized speech of 7 speakers from the UA-Speech database (Kim et al., 2008). This corpus was constructed with the aim of developing large-vocabulary dysarthric ASR systems which would allow users to enter unlimited text into a computer. All speakers exhibited symptoms of spastic dysarthria, according to an informal evaluation by a certified speech-language pathologist. Each speaker recorded 765 isolated words in 3 blocks of 255 words each; (a) common to all blocks: 10 digits (D), 19 computer commands (C), 26 radio alphabet letters (L), and 100 common words (CW) selected from the Brown corpus of written English; and (b) unique to each block: 100 uncommon words (UW) selected from children’s novels digitized by Project Gutenberg. Vocabularies D and CW were primarily composed of monosyllables, C and L of bisyllables, and UW of polysyllabic words. The speakers’ speech was affected by dysarthria associated with cerebral palsy. Data acquisition and intelligibility assessment is described in more detail in (Kim et al., 2008). Two hundred distinct words were selected from the recording of the second block: 10 digits, 25 radio alphabet letters, 19 computer commands and, 73 words randomly selected from each of the CW and UW categories. Five naive listeners were recruited for each speaker and were instructed to provide orthographic transcriptions of each word that they thought the speaker said. The percentage of correct responses was then averaged across five listeners to obtain each speakers intelligibility. Table 1 lists the speakers whose speech materials from the UA-Speech database were used, along with their human listener intelligibility ratings. The first letter of the speaker code (‘M’ or ‘F’) indicates their gender.

| Speaker | Age | Speech Intelligibility (%) |
|---------|-----|----------------------------|
| M09     | 18  | high (86%)                 |
| M05     | 21  | mid (58%)                  |
| M06     | 18  | low (39%)                  |
| F02     | 30  | low (29%)                  |
| M07     | 58  | low (28%)                  |
| F03     | 51  | very low (6%)              |
| M04     | >18 | very low (2%)              |

Table 1: Summary of Speaker Information (in decreasing order of human listener intelligibility rating).

For building the “MAP prior” speaker-independent system, the unadapted HMMs were trained on speech from the TIMIT corpus (Garofolo et al., 1993).

2.3 System Configurations

Table 2 lists the characteristics of the various system configurations that were studied: SD stands for speaker-dependent, SA for speaker-adapted; LR implies use of strictly left-to-right HMMs, TI for transition-interpolated HMMs; ‘m’, ‘v’, ‘w’, ‘t’ respectively denote means, variances, mixture-
component weights and transition probabilities.
These systems were developed for each of the seven

| System (Type) | HMM   | Parameters adapted |
|---------------|-------|--------------------|
| C00 (SD)      | LR    | —                  |
| C01 (SD)      | TI    | —                  |
| C11 (SA)      | LR    | m                  |
| C12 (SA)      | LR    | m,v                |
| C13 (SA)      | LR    | m,v,w              |
| C14 (SA)      | LR    | m,v,w,t            |
| C15 (SA)      | TI    | m,v,w,t            |

Table 2: Summary of ASR System Configurations

speakers listed in Table 1, and employed word-
internal, context-dependent triphone HMMs, with
three hidden states and observations modeled as
mixture-of-Gaussians. Configuration C00 was
developed by Sharma and Hasegawa-Johnson (2009)
and is the baseline configuration for the present
experiments. For configurations C11 through C15,
the speaker-independent systems trained on TIMIT
employed left-to-right HMMs. For systems C15,
the transition-interpolation was performed after ob-
taining the speaker-independent TIMIT-trained left-
to-right HMMs and before adaptation to the UA-
Speech speaker’s data: the original non-zero entries
in the transition probability matrices were scaled
down so that the sum of each row was unity after
changing the zero-entries to $\epsilon$. For each speaker, all
of blocks 1 and 3 were used as training data (sys-
tems C00, C01) or adaptation data (systems C11-
C15) and all of block 2 was used for testing. The
speaker-independent system was trained on all of
TIMIT’s training data and was tested on speech of
32 randomly chosen speakers from its test data.

The features extracted from the speech waveform
comprised of 12 Perceptual Linear Prediction co-
efficients (Hermansky, 1990) for 25 ms Hamming-
windowed segments obtained every 10 ms, plus the
energy of the windowed segment. ‘Velocity’ and
‘Acceleration’ components were also calculated for
this 13-dimensional feature, which finally resulted
in a 39-dimensional acoustic feature vector.

The measure used for assessing the performance
of the developed recognizers is the fraction of task-
vocabulary words correctly recognized (in percent),
edefined in Equation 1.

$$PWC = \frac{\# \text{words correctly recognized}}{\# \text{words attempted}} \times 100$$

(1)

For each configuration, the number of Gaussian
components in the state-specific observation proba-
bility densities was increased (in an iterative man-
ner) in powers of 2, from 1 to 32 components (for
C00 and C01) or 64 components (for C11-C15):
standard methods for choosing this number (using
development test data) could not be employed on
account of insufficient data. The results reported
in the next section should therefore be interpreted
development test results. In order to avoid over-
tuning, the number of Gaussian components was
constrained to be the same across all speakers. For
the speaker-dependent systems (C00 and C01), re-
sults are for HMMs with 2 Gaussian components per
probability density. For the speaker-adapted systems
(C11-C15), results are for HMMs with 32 Gaussian
components per probability density: while train-
ing the speaker-independent TIMIT system, it was
found that the phone recognition accuracy increased
monotonically when going from 1 to 32 Gaussian
components but decreased when going from 32 to
64 components.

3 Results

Tables 3, 4 list the PWC scores for the various sys-
tem configurations developed. The speakers are
listed in decreasing order of intelligibility rating.
The scores for systems C00 are restated here from
Sharma and Hasegawa-Johnson (2009) (Table 6, un-
der the column ‘T10’).

We see that speaker-dependent systems with left-
to-right HMMs (C00) have higher recognition ac-
curacy than the speaker-dependent systems with
transition-interpolated HMMs (C01), for all speak-
ers except M06. System C11 for a particular
speaker, with adaptation of Gaussian means alone
performs either better or worse than both sys-
tems C00 and C01 for that speaker. System C12
with adaptation of Gaussian means and variances,
has better recognition accuracy than both speaker-
dependent systems, for all speakers except F02 and
M07 (worse than both speaker-dependent systems).
System C13 with adaptation of all parameters ex-
Table 3: PWC scores for each speaker’s configurations C00-C12.

| Speaker | C00  | C01  | C11  | C12  |
|---------|------|------|------|------|
| M09     | 52.04| 47.3 | 57.1 | 62.1 |
| M05     | 35.52| 33.7 | 31   | 39.4 |
| M06     | 34.01| 36.1 | 38.6 | 38.5 |
| F02     | 35.06| 32.8 | 20.8 | 26.9 |
| M07     | 43.87| 40.7 | 32   | 35.9 |
| F03     | 12.61| 11.3 | 17.4 | 22.2 |
| M04     | 2.82 | 1.7  | 3.7  | 4.2  |

Table 4: PWC scores for each speaker’s configurations C00,C13-C15.

| Speaker | C00  | C13  | C14  | C15  |
|---------|------|------|------|------|
| M09     | 52.04| 66.4 | 65.8 | 64.2 |
| M05     | 35.52| 45.2 | 44   | 38.1 |
| M06     | 34.01| 40.7 | 40.1 | 39.2 |
| F02     | 35.06| 30.4 | 29.7 | 26.6 |
| M07     | 43.87| 43   | 41.8 | 35.9 |
| F03     | 12.61| 27.7 | 26.2 | 25.7 |
| M04     | 2.82 | 4.2  | 3.8  | 3.1  |

except transition-probabilities has the highest recognition accuracy for all subjects except F02 and M07 (highest among speaker-adapted systems only). System C14 which adapts all parameters including transition probabilities, always performs worse than the corresponding system C13, for all speakers. However, like system C13, it has better recognition accuracy than both speaker-dependent systems for all speakers except F02 and M07. Finally, performing transition-interpolation and adaptation of all parameters (system C15) worsens the performance to below that of the corresponding system C14; additionally, C15 has better recognition accuracy than both speaker-dependent systems whenever the corresponding C13 (and C14) system also performs better than them.

These results are plotted in Fig. 4 along with the human listeners’ intelligibility ratings of these speakers (the black circles). For speakers M09 and M05, system C13 with the best overall PWC score is still far from doing as well as human listeners. For

| Speaker | C00  | C01  | C11  | C12  |
|---------|------|------|------|------|
| M09     | 52.04| 47.3 | 57.1 | 62.1 |
| M05     | 35.52| 33.7 | 31   | 39.4 |
| M06     | 34.01| 36.1 | 38.6 | 38.5 |
| F02     | 35.06| 32.8 | 20.8 | 26.9 |
| M07     | 43.87| 40.7 | 32   | 35.9 |
| F03     | 12.61| 11.3 | 17.4 | 22.2 |
| M04     | 2.82 | 1.7  | 3.7  | 4.2  |

Figure 4: PWC scores for various system configurations (the black circles indicate speakers’ human listener intelligibility ratings).

the remaining subjects, it has however been able to do as well or better than human listeners even when it performed worse than the corresponding speaker-dependent systems (C00,C01): in fact, for speaker M06, it does better than human listeners when the speaker-dependent systems don’t.

Fig. 5 plots, for all speakers, the percentage difference $PWC(x)/PWC(C00)-1$ between the PWC of system $x$ ($x \in \{C01\}$) and the PWC of system C00.

| Speaker | C01  | C11  | C12  | C13  | C14  | C15  |
|---------|------|------|------|------|------|------|
| M09     | 52.04| 66.4 | 65.8 | 64.2 |
| M05     | 35.52| 45.2 | 44   | 38.1 |
| M06     | 34.01| 40.7 | 40.1 | 39.2 |
| F02     | 35.06| 30.4 | 29.7 | 26.6 |
| M07     | 43.87| 43   | 41.8 | 35.9 |
| F03     | 12.61| 27.7 | 26.2 | 25.7 |
| M04     | 2.82 | 4.2  | 3.8  | 3.1  |

Figure 5: Percentage change in PWC scores for various system configurations relative to configuration C00’s PWC score.

For speakers who have an intelligibility rating above 35% or below 25%, the speaker-adapted systems generally do better than their speaker-dependent counterparts. System C01, with transition interpolation, performs worse than system
C00 for all speakers except M06. The surprising result though is that for speakers with highly severe dysarthria (F03 and M04), speaker-adapted systems have substantially better recognition accuracies than their speaker-dependent counterparts, when previous studies have indicated that for such subjects, speaker-dependent systems perform better than speaker-adapted systems.

4 Conclusions

This study investigated adaptation and state-transition interpolation techniques for medium vocabulary HMM-based speech recognition of talkers with spastic dysarthria. It was found that performing transition-interpolation generally worsens recognition performance when compared to left-to-right HMMs. Performing both adaptation and transition-interpolation results in higher recognition accuracy compared to the speaker-dependent system with left-to-right HMMs but adaptation-only systems have still better performance. This implies that state-transitions not accounted for in left-to-right HMMs do not capture (or capture rather poorly) the outlier events that differentiate dysarthric speech from unimpaired speech at the sub-phone level.

The most interesting outcome of our experiments is that for subjects that have very severe dysarthria, speaker-adaptation was able to achieve substantial improvement in recognition accuracy, compared to the speaker-dependent systems. This finding is significant in that it is contrary to the conclusions of previously published studies. The results reported in this paper therefore suggest that the severity of dysarthria as quantified by the subject’s intelligibility rating is not a sufficient indicator of the relative performance of speaker-dependent and speaker-adapted systems.

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