On using Articulatory Features for Discriminative Speaker Adaptation

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Abstract
This paper presents a way to perform speaker adaptation for automatic speech recognition using the stream weights in a multi-stream setup, which included acoustic models for “Articulatory Features” such as \textit{ROUNDED} or \textit{VOICED}. We present supervised speaker adaptation experiments on a spontaneous speech task and compare the above stream-based approach to conventional approaches, in which the models, and not stream combination weights, are being adapted. In the approach we present, stream weights model the importance of features such as \textit{VOICED} for word discrimination, which offers a descriptive interpretation of the adaptation parameters.

1 Introduction
Almost all approaches to automatic speech recognition (ASR) using Hidden Markov Models (HMMs) to model the time dependency of speech are also based on phones, or context-dependent sub-phonetic units derived from them, as the atomic unit of speech modeling. In phonetics, a phone is a shorthand notation for a certain configuration of underlying articulatory features (AFs) (Chomsky and Halle, 1968): /p/ is for example defined as the unvoiced, bi-labial plosive, from which /b/ can be distinguished by its \textit{VOICED} attribute. In this sense, instead of describing speech as a single, sequential stream of symbols representing sounds, we can also look at speech as the result of a process involving several parallel streams of information, each of which describes some linguistic or articulatory property as being either absent or present.

A multi-stream architecture is a relatively simple approach to combining several information sources in ASR, because it leaves the basic structure of the Hidden Markov Model and its computational complexity intact. Examples combining different observations are audio-visual speech recognition (Potamianos and Graf, 1998) and sub-band based speech processing (Janin et al., 1999). The same idea can also be used to combine different classifiers on the same observation. In a multi-stream HMM setup, \textit{log-linear interpolation} (Beyerlein, 2000) can be derived as a framework to integrating several independent acoustic models given as Gaussian Mixture Models (GMMs) into the speech recognition process: given a “weight” vector $\Lambda = \{\lambda_0, \lambda_1, \cdots, \lambda_M\}$, a word sequence $W$, and an acoustic observation $o$, the posterior probability one wants to optimize is written as:

$$p(W|o) = C \exp \left\{ \sum_{i=0}^{M} \lambda_i \log p_i(W|o) \right\}$$

$C$ is a normalization constant, which can be neglected in practice, as long as normalization $\sum_i \lambda_i = \text{const}$ is observed. It is now possible to set $p(W|o) \propto p(o|W)$ (Beyerlein, 2000) and write a speech recognizer’s acoustic model $p(o|W)$ in this form, which in logarithmic representation reduces to a simple weighted sum of so-called “scores” for each individual stream. The $\lambda_i$ represent the “im-
portance” of the contribution of each individual in-
formation source.

Extending Kirchhoff’s (Kirchhoff, 1999) ap-
proach, the log-likelihood score combination
method to AF-based ASR can be used to combine
information from $M$ different articulatory features
while at the same time retaining the “standard”
acoustic models as stream 0. As an example
using $M = 2$, the acoustic score for /z/ would
be computed as a weighted sum of the scores for
a (context-dependent sub-)phonetic model $z$, the
score for FRICATIVE and the score for VOICED,
while the score for /s/ would be computed as a
weighted sum of the scores for a (context-dependent
sub-) phonetic model $s$, the score for FRICA-
TIVE and the score for NON_VOICED. The free
parameters $\lambda_i$ can be global (G), or they can be
made state-dependent (SD) during the optimization
process, thus changing the importance of a feature
given a specific phonetic context, as long as overall
normalization is observed. (Metze, 2005) discusses
this stream setup in more detail.

2 Experiments

To investigate the performance of the proposed AF-
based model, we built acoustic models for 68 ar-
ticulatory features on 32h of English Spontaneous
Scheduling Task ESST data from the Verbmobil
project (Wahlster, 2000), and integrated them with
matching phone-based acoustic models.

For training robust baseline phone models, 32h
from the ESST corpus were merged with 66h Broad-
cast News ’96 data, for which manually annotated
speaker labels are available. The system is trained
using 6 iterations of ML training and uses 4000 con-
text dependent (CD) acoustic models (HMM states),
32 Gaussians per model with diagonal covariance
matrices and a global semi-tied covariance matrix
(STC) in a 40-dimensional MFCC-based feature
space after LDA. The characteristics of the training
and test sets used in the following experiments are
summarized in Table 1.

The ESST test vocabulary contains 9400 words
including pronunciation variants (7100 base forms)
while the language model perplexity is 43.5 with an
out of vocabulary (OOV) rate of 1%. The language
model is a tri-gram model trained on ESST data
containing manually annotated semantic classes for
most proper names (persons, locations, numbers).
Generally, systems run in less than 4 times real-time
on Pentium 4-class machines. The baseline Word
Error Rate is reported as adaptation “None” in Ta-
ble 2; the system parameters were optimized on the
ds2 data set. As the stream weight estimation pro-
cess can introduce a scaling factor for the acoustic
model, we verified that the baseline system can not
be improved by widening the beam or by readjust-

Table 1: Data sets used in this work: The ESST test
set 1825 is the union of the development set ds2
and the evaluation set xv2.

| Data Set | Train | Test |
|----------|-------|------|
| Duration | 98h   | 2h25 | 1h26 | 0h59 |
| Utterances | 39100 | 1825 | 1150 | 675  |
| Recordings | 8681  | 58   | 32   | 26   |
| Speakers  | 423   | 16   | 9    | 7    |
stream weights, i.e. weights which do not depend on state or context.

2.2 Speaker-specific Stream Weights

The ESST test 1825 set is suitable to test speaker-specific properties of articulatory features, because it contains 16 speakers in 58 different recordings. As 1825 provides between 2 and 8 dialogs per speaker, it is possible to adapt the system to individual speakers in a “round-robin” or “leave-one-out” experiment, i.e. to decode every test dialog with weights adapted on all remaining dialogs from that speaker in the 1825 test set. Using speaker-specific, but global (G), weights computed with the above settings, the resulting WER is 21.5% (row “AF (G) on speaker” in Table 2).

Training parameters were chosen to display improvements after the first iteration of training without convergence in further iterations. Consequently, training a second iteration of global (i.e. context independent) weights does not improve the performance of the speaker adapted system. In our experiments we reached best results when computing state-dependent (SD) feature weights on top of global weights using the experimentally determined smaller learning rate of $\epsilon_{SD} = 0.2 \cdot \epsilon$. In this case, speaker and state dependent AF stream weights further reduce the word error rate to 19.8% (see bottom row of Table 2).

2.3 ML Model Adaptation

When training speaker-dependent articulatory feature weights in Section 2.2, we were effectively performing supervised speaker adaptation (on separate adaptation data) with articulatory feature weights. To compare the performance of AFs to other approaches to speaker adaptation, we adapted the baseline acoustic models to the test data using supervised maximum likelihood linear regression (MLLR) (Leggetter and Woodland, 1994) and constrained MLLR, which is also known as “feature-space adaptation” (FSA) (Gales, 1997).

The ESST data has very little channel variation so that the performance of models that were trained on both ESST and BN data can be improved slightly on ESST test dialogs by using FSA, while MLLR already leads to over-specialization (Table 2, rows “FSA/ MLLR on ds2”). The results in Table 2 show that AF adaptation performs as well as FSA in the case of supervised adaptation on the ds2 data and better by about 1.3% absolute in the speaker adaptation case, despite using significantly less parameters (69 for the AF case vs. 40*40=1.6k for the FSA case). While supervised FSA is equivalent to AF adaptation when adapting and decoding on the ds2 data in a “cheating experiment” for diagnostic purposes (22.5% vs 22.6%, rows “FSA/ AF (G) on ds2” of Table 2), supervised FSA only reaches a WER of 22.8% on 1825 when decoding every ESST dialog with acoustic models adapted to the other dialogs available for this speaker (row “FSA on speaker”). AF-based adaptation reaches 21.5% for the global (G) case and 19.8% for the state dependent (SD) case (last two rows). The AF (SD) case has 68*4000=276k free parameters, but decision-tree based tying using a minimum count reduces these to 4.3k per speaker. Per-speaker MLLR uses 4.7k parameters in the transformation matrices on average per speaker, but performs worse than AF-based adaptation by about 1% absolute.

2.4 MMI Model Adaptation

In a non-stream setup, discriminative speaker adaptation approaches have been published using conditional maximum likelihood linear regression (CM-LLR) (Gunawardana and Byrne, 2001) and MMI-
MAP (Povey et al., 2003). In supervised adaptation experiments on the Switchboard corpus, which are similar to the experiments presented in the previous section, CMLLR reduced word error rate over the baseline, but failed to outperform conventional MLLR adaptation (Gunawardana and Byrne, 2001), which was already tested in Section 2.3. We therefore compared AF-based speaker adaptation to MMI-MAP as described in (Povey et al., 2003).

The results are given in Table 2: using a comparable number of parameters for adaptation as in the previous section, AF-based adaptation performs slightly better than MMI-MAP (19.8% WER vs. 20.5%; rows “MMI-MAP/ AF (SD) on speaker”). When testing on the adaptation data $\text{ds}_2$ as a diagnostic experiment, MMI-MAP as well as MLLR outperform AF based adaptation, but the gains do not carry over to the validation set $\text{sv}_2$, which we attribute to over-specialization of the acoustic models (rows “MLLR/ MMI-MAP/ AF (SD) on $\text{ds}_2$”).

3 Summary and Conclusion

This paper presented a comparison between two approaches to discriminative speaker adaptation: speaker adaptation using articulatory features (AFs) in the multi-stream setup presented in (Metze, 2005) slightly outperformed model-based discriminative approaches to speaker adaptation (Gunawardana and Byrne, 2001; Povey et al., 2003), however at the cost of having to evaluate additional codebooks in the articulatory feature streams during decoding. In our experiments, we used 68 AFs, which requires the evaluation of 68 models for “feature present” and 68 models for “feature absent” for each frame during decoding, plus the computation necessary for stream combination. In this setup however, the adaptation parameters, which are given by the stream combination weights, have an intuitive meaning, as they model the importance of phonological features such as VOICED or ROUNDED for word discrimination for this particular speaker and phonetic context. Context-dependent stream weights can also model feature asynchrony to some extent, so that this approach not only improves automatic speech recognition, but might also be an interesting starting point for future work in speaker clustering, speaker identification, or other applications in speech analysis.

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