Towards Consistent Hybrid HMM Acoustic Modeling

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Abstract

High-performance hybrid automatic speech recognition (ASR) systems are often trained with clustered triphone outputs, and thus require a complex training pipeline to generate the clustering. The same complex pipeline is often utilized in order to generate an alignment for use in frame-wise cross-entropy training. In this work, we propose a flat-start factored hybrid model trained by modeling the full set of triphone states explicitly without relying on clustering methods. This greatly simplifies the training of new models. Furthermore, we study the effect of different alignments used for Viterbi training. Our proposed models achieve competitive performance on the Switchboard task compared to systems using clustered triphones and other flat-start models in the literature.

Index Terms: CART-free hybrid HMM, full-sum, Baum-Welch, Viterbi

1. Introduction

One of the early applications of neural networks (NNs) in automatic speech recognition (ASR) task was within the hidden Markov model (HMM) framework \cite{1}. By defining a set of states which cannot be observed, the HMM establishes a relation between a given sequence of features or observations and the sequence of output symbols. The likelihood of generating a feature observation given a state, originally estimated by a Gaussian mixture model (GMM), is replaced in the hybrid approach by normalized scaled state posteriors estimated by a neural model. The HMM labels for the states are context-dependent units, such as triphones, i. e., phonemes augmented with their left and right phonetic contexts. Due to the large number of triphone state labels and for a robust parameter estimation, the states are usually clustered with classification and regression trees (CART) \cite{2}. The Viterbi training of the hybrid model also requires an initial alignment of the tied-states to the acoustic features, typically obtained from a previously trained GMM. Moreover, the overall system in the standard configuration makes use of a pronunciation lexicon, a phoneme inventory, and a language model. The aforementioned components of the hybrid system require several training stages and do not allow for a consistent and unified acoustic modeling. The end-to-end (E2E) encoder-decoder models \cite{3,4,5,6} on the other hand offer the possibility of carrying out a joint optimization of different components, by directly transforming a sequence of feature vectors representing the speech signal, to a sequence of characters or wordpieces. Despite the recent advances in E2E modeling \cite{7,8,9}, hybrid models continue to be competitive \cite{10,11}. Moreover, in the speech community, their advantage is often underlined when low-resource tasks are involved. Recently it was also shown that for the domain adaptation tasks with acoustic or content mismatch the hybrid approach can lead to larger improvements, so far \cite{12}.

In our previous work\cite{13}, we proposed the factored hybrid model: a context-dependent (CD) HMM/NN hybrid model that does not use phone clustering for the computation of label posteriors. We showed that given an existing alignment from a tandem system\cite{14}, it is possible to attain similar performance as a CART based system. In this work, we take a further step towards the possible elimination of the system dependency on an external alignment. Specifically, we do a two-fold investigation: (1) flat-start\textsuperscript{1} training of a monophone factored hybrid, (2) Multi-stage phonetic training of our proposed triphone with fixed path and frame-wise cross-entropy (CE), starting with different alignments. There are multiple early works in the literature which propose hybrid models trained with the full-sum criterion, i. e. without the Viterbi approximation\cite{15,16,17}. In these works it has been argued that the soft alignment on the frame level is more useful for ASR, because of the inherently fuzzy nature of phoneme boundaries and the overlap in the windows used for the feature extraction. Today, with bidirectional Long Short-Term Memory (Bi-LSTM) based encoders, as argued in \cite{19}, the scenario has slightly changed. There is an additional issue with one label dominating the learned alignments due to the access of the encoder to the full sequence. Moreover, the training of a network which starts from scratch can be unstable. So far, with the exception of the work using Time-Delay NN\cite{20}, none of the prior works considered the unclustered set of states for full-sum training of hybrid model. In addition to the proposed flat-start factored hybrid, the objective of our current work is also to study the behavior of our models with respect to the choice of different alignments in CE training with Viterbi. It is important to note that in this paper we apply a simplifying assumption in our full-sum training objective, as described in Sec. \ref{sec:2}. In the next sections we will present our framework and the models, followed by experimental results and our conclusions.

2. Modeling Framework and Training

2.1. Standard Hybrid Approach

The statistical formulation of the ASR task maximizes the posterior probability of the word sequence \(w^N\) given the input features \(x^T\), with \(T \gg N\), based on the Bayes decision rule \cite{21}, as follows:

\[
x^T \rightarrow w^N(x^T) = \arg \max_{N,w} \left\{ p(w^N|x^T) \right\}
= \arg \max_{N,w} \left\{ p(x^T|w^N) \cdot p(w^N) \right\}
\] (1a)

The acoustic component \(p(x^T|w^N)\) in Eq. (1a) modeling the probability of observing this feature sequence given a word sequence, in the HMM framework can be rewritten as follows:

\textsuperscript{1}We borrow this terminology from \cite{15}, and use it for denoting a GMM-free hybrid model built from scratch.
where after summing over all possible hidden state sequences, we apply Markov and output independence assumptions and factorize into emission and state transition probabilities. As a further model assumption we substitute the summation with maximization, for a Viterbi decoding [22]. Moreover, \( \phi_1^t \) is the triphone sequence of length \( M \) corresponding to the word sequence. For simplicity, here the pronunciation distribution can be assumed to be deterministic.

### 2.2. Direct Modeling of Context

In the standard hybrid model \( s \) corresponds to the labels of the respective cluster of tied-states. In our case, we do not tie the labels. With similar notation to [19], denote by \( \{ \phi_t, \sigma_c, \phi_r \} \) the set of left, center and right phonomes of the aligned triphone at time frame \( t \). We model the triphone state at time frame \( t \) explicitly by means of a state class \( c(s_t, w^N_t) = \{ \phi_{c_t}, \phi_{o_t}, \phi_{r_t} \} \), where \( i \) enumerates the HMM state of the corresponding triphone. Define \( p_\ell \) to be the parametrized probability distribution at time frame \( t \). The emission probability of Eq. (3) can now be reformulated as follows:

\[
p(x_t | s_t, \phi_i^M, w^N_t) = p(x_t | c(s_t, w^N_t)) = p_i(x_t | \phi_{c_t}, \phi_{o_t}, \phi_{r_t})
\]

For simplicity, we define \( \sigma_c = (\phi_{c_t}, i) \) to be the center phoneme state identity. For notational simplicity, the likelihood of observing a feature vector \( x_t \) is consequently written as:

\[
p(x_t | \phi_{c_t}, \phi_{o_t}, \phi_{r_t}, i) = p_i(x_t | \phi_{c_t}, \phi_{o_t}, \phi_{r_t})
\]

By using the usual substitution in the hybrid approach via Bayes identity, it is possible to replace \( p(x_t | \phi_{c_t}, \phi_{o_t}, \phi_{r_t}) \) by the locally normalized joint probability of Eq. (3), with class-conditional acoustic model (AM) and prior scales, \( \alpha \) and \( \beta \).

\[
p_i(x_t | \phi_{c_t}, \sigma_c, \phi_r) = \frac{p_i(\phi_{c_t}, \sigma_c, \phi_r | x_t) \cdot p_i(x_t)}{p(\phi_{c_t}, \sigma_c, \phi_r)} \\
\sim \frac{p_i(\phi_{c_t}, \sigma_c, \phi_r | x_t)^{\alpha_i}}{p(\phi_{c_t}, \sigma_c, \phi_r)^{\beta_i}}
\]

(3a)

The resulting state labels refer to the simple enumeration of all possible triphone states, where the identity of each state is uniquely defined by its position within the center phoneme and its right and left contexts. Given that in our case each phoneme consists of three HMM states, we would need \( n = 3 \times |\text{phonemes}|^3 \) softmax outputs, e.g., around 300k for the Switchboard task, for the joint posterior in numerator of Eq. (3). Different early works on CD hybrid models tried to address this issue by using factored neural networks [23][24]. However, the joint posterior probability modeled by the mentioned works still takes into account the set of clustered states. Depending on the type of context we want to model, it is possible to carry out different factorizations. We consider two main CD models and a monophone model as described in the following paragraphs. The monophone model is relevant in our work for two reasons: (1) a multi-stage phonetic training with regularization effect on the model performance, (2) an initial study presented in this work on full-sum training of a hybrid model without state-tying.

#### 2.2.1. Decision Rules

The decoding of our CD and monophone models relies on the application of Eq. (2) via the suitable factorization of the joint posterior obtained in Eq. (3a). Each factor refers to a softmax output belonging to the context-dependent neural network trained in a multi-task manner, either with full-sum or with the fixed best path. The architectures of different models are depicted in Fig. [1]. Each decision rule consists of a subset of the trained outputs and is defined following the mathematically sound factorization and definition of dependencies. This means, the trained model can have additional outputs that are not used during decoding. Moreover, we set AM scale \( \alpha \) to one and define separate prior scales for each CD prior in the denominator. Among different possible decompositions, for our triphone model we consider a left-to-right trigram, via a forward decomposition.

\[
p_i(x_t | \phi_{c_t}, \sigma_c, \phi_r) \sim \frac{p_i(\phi_{c_t}, \sigma_c, \phi_r | x_t) p_i(x_t)}{p(\phi_{c_t}, \sigma_c, \phi_r)^{\beta_i}}
\]

(4a)

For the monophone models presented in this work we only use the center state phoneme, as shown in Eq. (5). Moreover, we add the dependency to the left context for diphone models, as described in Eq. (6).

\[
p_i(x_t | \phi_{c_t}, \sigma_c, \phi_r) \sim \frac{p_i(\phi_{c_t}, \sigma_c, \phi_r | x_t) p_i(x_t)}{p(\phi_{c_t} | \sigma_c, \phi_r)^{\beta_i}}
\]

(5)

\[
p_i(x_t | \sigma_c, \phi_r) \sim \frac{p_i(\sigma_c, \phi_r | x_t) p_i(x_t)}{p(\phi_{c_t} | \sigma_c, \phi_r)^{\beta_i}}
\]

(6)

### 2.3. Training Criteria

#### 2.3.1. Flat-Starting

The maximum log likelihood criterion for training the acoustic model of Eq. (1a), modeled with the set of parameters \( \theta \), is defined as:

\[
\max_{\theta} \{ \log L(\theta) \} := \max_{\theta} \left\{ \log p(x_T | w^N_\theta, \theta) \right\}
\]

(7)

We calculate the derivative similarly to [19]. We choose as our starting point the following formulation used in the standard hybrid approach, with \( c(s) \) and \( \gamma(c(s) | x_T, w^N_\theta) \) being the CART label and its posterior occupancy, respectively:

\[
\frac{\partial}{\partial \theta} \log L(\theta) = \sum_{t \in c(s)} \gamma_t(c(s) | x_T, w^N_\theta, \theta) \frac{\partial}{\partial \theta} \log p_i(x_t | c(s), \theta)
\]

By limiting the summation over the set of valid state sequences corresponding to the set of word sequences, we have:

\[
\gamma_t(c(s) | x_T, w^N_\theta, \theta) = \sum_{t \in c(s)} \gamma_t(c(s) | x_T, \theta) \frac{\partial}{\partial \theta} \log p_i(x_t | c(s), \theta)
\]

(8)

In our proposed approach, we plug in our definition of a state class, as described in Sec. 2.2 and carry out the factorization for a triphone model with forward decomposition. This leads to separate factors for the log probabilities, each weighted by the state class occupancy. The latter can then be marginalized over all random variables that differ from the one occurring in the log probability. This will lead to three different gamma values \( \gamma(z) \), for \( z \in \{ \phi_t, \sigma, \phi_r \} \), that we denote as left context, center state and right context occupancy, respectively. Moreover, as an initial study case, we apply a simplifying assumption for the log probabilities by considering the dependency only on the input signal and not the other phonetic or phoneme state entities, as shown in Eq. (6). The training procedure consequently is similar to a generalized Expectation-Maximization algorithm, where we iteratively alternate the estimation of the contexts and center state occupancies with the NN backpropagation step.
\[
\frac{\partial}{\partial \theta} \log L(\theta) = \sum_{t, (\phi_t, \sigma_t, \phi_x)} \gamma_t((\phi_t, \sigma_t, \phi_x)|x_t^i, w_t^N, \theta) \cdot \frac{\partial}{\partial \theta} \log p_{\theta}(x_t|\phi_t, \sigma_t, \phi_x)
\]

\[
\sum_{t, (\phi_t, \sigma_t, \phi_x)} \gamma_t((\phi_t, \sigma_t, \phi_x)|x_t^i, w_t^N, \theta) \cdot \frac{\partial}{\partial \theta} \log p_{\theta}(x_t|\phi_t, \sigma_t, \phi_x)
\]

(8a)

It is possible to approximate the sum over the hidden state sequences in Eq. (8a) with the maximum and use Viterbi. Instead of maximizing the likelihood of the observed data, Viterbi training maximizes the probability of the most likely state sequence. In this case, \( \gamma_t(c,s) \) is one-hot encoding of the state class aligned in the best path. The best path calculated with Viterbi approximation can be kept fixed for all epochs and can be derived from external sources. The model is trained using frame-wise cross-entropy. We compare the Viterbi training with fixed path starting with alignments from both GMM based systems and our proposed forced-aligned flat-start CD model. Moreover, the CD models using Viterbi and unclustered set of states use pre-training on phonetic level [13].

3. Experimental results

All models are trained and evaluated on 300h Switchboard-1 Release 2 (LDC97S62) [27] and Hub’00 data (LDC2002S09), respectively, with the aid of RETURNN and RASR toolkits [28, 29]. The Forward-Backward algorithm for computation of the soft alignments in the flat-start model, i.e., contexts and center state occupancies, makes use of a modified version of the CUDA based implementation presented in [19].

All experiments share the same front-end architecture based on a Bi-LSTM encoder comprising 6 forward and backward layers of size 500 with 10\% dropout probability [30]. The input speech signal to the encoder is represented by 40-dimensional Gammatone Filterbank features [31], extracted from 25 milliseconds (ms) analysis frames with 10ms shift. Concerning the CD architectures, the one-hot encoding of the left and/or right phonemes and the center phoneme states are projected by using linear layers of dimension 10 and 30, respectively. Our proposed approach makes use of a state inventory consisting of three times number of phonemes plus the single-state silence entity. For the standard hybrid, a set of 9001 CART labels are considered. All models using Viterbi and fixed path share the same set of training hyper-parameters and are trained with the frame-wise CE criterion. During CE training, the sequences are divided into chunks of length 128 with 50\% overlap. The chunking reduces overfitting as the model has access to a smaller context window during training and speeds up training. The full-sum training does not allow for chunking. The parameters for the flat-start model trained with full-sum (FS) differ, as described below. All models are trained by using an Adam optimizer with Nesterov momentum [32]. We use Newbob learning rate (LR) scheduling to reduce the initial LR of (CE: 1e\(^{-3}\), FS: 5e\(^{-4}\)) with a decay factor of (CE: 0.9, FS: \(\sqrt{0.8}\)) based on (CE: frame error rate, FS: posterior scores) to a minimum value of (CE: 2e\(^{-5}\), FS: 1e\(^{-6}\)). For further regularization, we use L2 weight decay with a scale of 0.01, gradient noise [33] with a variance of (CE: 0.1, FS: 0.3) and focal loss factor of 2.0 [34]. We normalize the state posteriors with the prior during full-sum training and during recognition of all models. During training, the prior estimation is done on-the-fly with exponential decaying average. The AM and prior scales for full-sum training starts with 0.01 and 0.1, respectively and grows at each epoch. We set maximum values of 0.3 for AM scale, together with 0.3 and 0.4 for left and right contexts priors, and 0.7 for center state phoneme prior. In [19], it is argued that if during full-sum training we do not apply state priors, the alignment will be dominated by silence. In our case, by using separate priors for each factor, we observed that the alignment contains very little silence compared to alignments from both GMM monophone and tandem systems. For recognition, priors are estimated by averaging over the output activations of the network using a subset of the training set. We utilize both 4-gram and LSTM language models for decoding [35, 36, 37].

An overview of different alignments and their description can be found in Table 1. The GMM-Mono alignment derives from a monophone GMM system initialized with a linear alignment. For alignments taken from our factored hybrid models, we first train the monophone model of Fig. 1a, then we apply Viterbi and using GMM-Mono. By applying forced-alignment (F-Align),
we obtain the FH-Mono alignment. We then initialize a di-phone model with the parameters of this trained model and continue training with GMM-Mono. A further F-align step using this model provides FH-Di. In different conducted experiments, we observed that independently from the alignment used for Viterbi training, the multi-stage phonetic training, i.e., initializing an n-phone model with the parameters of an (n-1)-phone Viterbi training, the multi-stage phonetic training, i.e., initializing an n-phone model with the parameters of an (n-1)-phone model and training by resetting LR, leads always to improvement compared to standard hybrid with state-tying. We also showed that our context-dependent factored hybrid approach trained with full-sum training and state-tying. We also observed that relative better performance than the standard hybrid approach trained with full-sum and state-tying.

5. Acknowledgements

This project has received funding from the European Research Council (ERC) under the European Union’s Horizon 2020 research and innovation programme (grant agreement n\textsuperscript{°} 694537, project “SEQCLAS”). The work reflects only the authors’ views and the European Research Council Executive Agency (ERC) is not responsible for any use that may be made of the information it contains. The work was partly funded by the Google Faculty Research Award for “Label Context Modeling in Automatic Speech Recognition”. Authors thank Wilfried Michel for insightful comments.
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