Implicit Trajectory Modeling through Gaussian Transition Models

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Abstract

It is well known that frame independence assumption is a fundamental limitation of current HMM based speech recognition systems. By treating each speech frame independently, HMMs fail to capture trajectory information in the acoustic signal. This paper introduces Gaussian Transition Models (GTM) to model trajectories implicitly. Comparing to alternative approaches such as segment modeling and parallel path HMM, GTM has the advantage that it integrates seamlessly with the HMM framework; it can model a large number of trajectories; and there is no need to define a topology apriori. We present preliminary results on Switchboard, a large vocabulary conversational speech recognition task, demonstrating improved modeling and potential for improved recognition performance.

1 Motivation

Hidden Markov model (HMM) is the dominant approach in automatic speech recognition. Several assumptions are made in HMMs, one of which is frame independence: all speech frames are conditionally independent given the hidden state sequence. This makes HMMs ineffective in modeling trajectories.

Real speech process differs from random processes in that articulators move along a low dimensional manifold. As a result, speech trajectory is relatively smooth in the feature space. But HMM, as an generative model, does not necessarily generate a smooth sequence, due to the conditional independence assumption. This is best illustrated by considering a gender independent HMM, using Gaussian Mixture Model (GMM) for output densities (Figure 1). Assuming certain mixture components are trained on mostly male speakers, while other components of the same mixture are trained on mostly females, sampling the HMM will produce a sequence randomly switching between male and female at any frame.

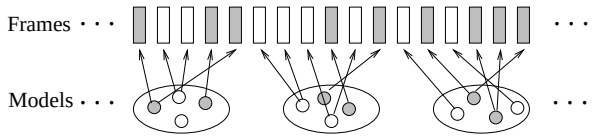


Figure 1: HMM-GMM as a generative model (shaded Gaussian models male speech, white stands for female.)

Variations in speaker, context and speaking mode can all produce completely different trajectories for the same phone. If modeled by a single state sequence as in a regular HMM, trajectories will be all mixed up, resulting in a model with poor discrimination between trajectories.

Segment models attempt to exploit time-dependencies in the acoustic signal (Ostendorf et al., 1996), by modeling trajectories either parametrically or non-parametrically. Since these approaches typically falls outside the HMM framework, they can not take full advantage of the efficient HMM training and recognition algorithms.

Iyer et al. proposed parallel path HMM (Iyer et al., 1998) which uses parallel paths to represent multiple trajectories. This stays inside the HMM framework. However, the number of parallel paths are normally quite limited (two or three). Choosing the right number of paths is also an unsolved problem.

In this paper, we propose a new approach called Gaussian Transition Model (GTM), which attempts to capture dependency between adjacent frames by modeling Gaussian transitions. GTM can potentially

model a large number of trajectories. It also fits nicely within the HMM framework. This paper is organized as follows. Section 2 introduces the notion of GTM. Section ?? describes the training algorithm. Section 4 presents preliminary experiment results.

2 Gaussian Transition Model

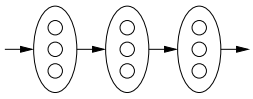
To introduce the idea of GTM, let's consider the probability of a sequence of frames $\boldsymbol{o}_1, \cdots, \boldsymbol{o}_T$ given a sequence of Gaussian mixture models $M_1, \cdots, M_T$:

$$p(\boldsymbol{o}_1, \cdots, \boldsymbol{o}_T | M_1, \cdots, M_T) = \prod_{t=1}^{T} p(\boldsymbol{o}_t | M_t)$$

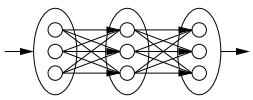
$$= \prod_{t=1}^{T} \sum_{k} \pi_{tk} g_{tk}(o_t) = \sum_{k_1} \sum_{k_2} \cdots \sum_{k_T} \prod_{t=1}^{T} \pi_{tk} g_{tk}(\boldsymbol{o}_t)$$

where $g_{tk}(\cdot)$ is the kth Gaussian in the tth model, π_{tk} is the mixture weight.

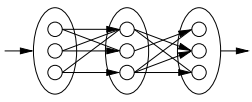
This is illustrated in Figure 2, where (a) shows the mixture model sequence, (b) shows the equivalent full Gaussian transition network. Think of each Gaussian g_{tk} as a modeling unit by itself, $\prod_t g_{tk}$ represents a unique trajectory, weighted by $\prod_t \pi_{tk}$. In the traditional HMM-GMM, all possible trajectories are allowed. Say some Gaussians model male speech, some model female speech, HMM-GMM allows trajectories that hops between the two genders in the middle of an utterance!



(a) linear sequence of mixture models



(b) the equivalent full Gaussian transition model



(c) constrained Gaussian transition model

Figure 2: Gaussian Transition Network

GTM restricts the set of allowable Gaussian transitions by modeling transition probabilities between Gaussians in adjacent states:

$$a_{ij} = P(q_t = g_j | q_{t-1} = g_i)$$

where a_{ij} is the probability of transition from Gaussian g_i to Gaussian g_j, subject to the constraint $\sum_j a_{ij} = 1$. Figure 2(c) shows a GTM after pruning away unlikely transitions.

2.1 GTM and Pronunciation Modeling for Sloppy Speech

As mentioned before, sloppy speech can yield different trajectory from careful, read speech. GTM provides a way to implicitly model sloppy pronunciation. Explicit pronunciation modeling (by adding alternative pronunciation to the lexicon) has so far been difficult, since many reductions are too subtle to be classified as either phoneme substitution or deletion. Partial reduction or partial realization may actually be better modeled at a sub-phoneme level. In this sense, Gaussian transition models can be thought of as pronunciation networks at the Gaussian level. Comparing to pronunciation modeling at either state level (Saraclar et al., 2000) or phoneme level, GTM provides better resolution.

3 Training GTM

When viewing each Gaussian as a state by itself, GTM can be readily trained using the existing Baum-Welch algorithm. Following notations of (Rabiner, 1989),

$$\gamma_t(i) = P(q_t = g_i) = \frac{\alpha_t(i)\beta_t(i)}{\sum_j \alpha_t(j)\beta_t(j)}$$

$$\begin{aligned} \xi_t(i,j) &= P(q_t = g_i, q_{t+1} = g_j) \\ &= \frac{\alpha_t(i) a_{ij} b_j(\boldsymbol{o}_{t+1}) \beta_{t+1}(j)}{\sum_i \sum_j \alpha_t(i) a_{ij} b_j(\boldsymbol{o}_{t+1}) \beta_{t+1}(j)} \end{aligned}$$

where α is the forward probability and β is the backward probability. The update formula is:

$$a_{ij} = \frac{\sum_t \xi_t(i,j)}{\sum_t \gamma_t(i)}$$

It can be shown that traditional HMM-GMM is a special case of GTM where $a_{ij} = \pi_j$ i.e. transition probability a_{ij} equals mixture weight of the destination Gaussian, independent of the identity of the source Gaussian. In other words, transition models are tied for all Gaussians in the same mixture.

In practice, GTM training faces two major issues: insufficient data and pruning.

3.1 Trainability

GTM can take a large number of parameters. First, transition between two mixtures of n components each requires n^2 transition probabilities. Second, in an LVCSR system with thousands of mixture models, transition can happen between many of them.

Hence data sufficiency becomes a concern. In our experiments, we choose to model only frequent transitions. For everything else, we backoff to the traditional HMM-GMM model: $a_{ij} = \pi_j$.

3.2 Pruning

Even in conventional HMM training, it is common for people to ignore transition probabilities. Their contribution to the overall score is quite small, comparing to observation probabilities (which is several orders of magnitude bigger in a continuous HMM). The same is true for Gaussian transition probabilities. While GTM training offers better discrimination between trajectories, all trajectories are nonetheless still permitted. Pruning away unlikely transitions leads to a more compact, and also a more prudent model. In reality, however, we need to exercise great care in pruning so as not to prune away unseen trajectories, due to a limited training set.

3.3 Computation

GTM training is computationally very demanding. A transition between two mixture models is now expanded to a full transition network between all Gaussians. In a system with 10 Gaussians per mixture, training takes 100 times longer.

4 Experiments

Experiments are carried out on the Switchboard (SWB) task using the Janus system (Soltau et al., 2002). We choose this task to evaluate the effect of GTM on modeling pronunciation variations. The test set is a 1 hour subset of the 2001 Hub5e evaluation set. Acoustic training uses a 66 hours subset of the SWB data. We use a 15k vocabulary and a trigram language model trained on SWB and CallHome. The acoustic model has roughly 6000 mixtures with a total of 86K Gaussians, on average 14 Gaussians per model.

We applied a two-tiered strategy to cope with the data sufficiency issue.

- Before training, we count the number of transitions for each model pair on the training data, using Viterbi alignment. Only transitions with counts above a certain threshold are modeled with GTM. Of about 6000 mixture models, a total of 40K model pairs (out of a potential 6Kx6K=36M) have been observed. It turns out that most of the transitions (72%) are transitions within the same model (corresponding to self-loop in HMM). We choose to model the most frequent 9400 model pairs with GTM. Not surprisingly, most of the 6000 same-model pairs are among those chosen.
- During training, we apply a minimum count criterion: only update a transition model if the Gaussian receives enough training counts.

One iteration of Baum-Welch training gives significant improvement in term of likelihood. Log likelihood per frame improves from -50.67 to -49.18, while conventional HMM training can only improve less than 0.1. Considering the baseline acoustic model has already reached the saturation point, this indicates improved acoustic modeling.

GTM transitions are pruned if their probabilities fall below a certain threshold (default is 1e-5). Table 1 shows word error rates for GTM models pruned against different thresholds. It is encouraging that best performance is obtained after pruning away almost 2/3 of all transitions.

Pruning Threshold	Avg. # Transitions per Gaussian	WER (%)
baseline	14.4	34.1
1e-5	9.7	33.7
1e-3	6.6	33.7
0.01	4.6	33.6
0.05	2.7	33.9

Table 1: Word error rates

5 Future Work

In this paper, we have presented Gaussian Transition Model, a new approach to model trajectories within the HMM framework. Preliminary experiments have shown encouraging improvements.

There are several possibilities for further improvements. First, when modifying the decoder to use GTM, Viterbi approximation is used at word boundaries, which means trajectory information will be lost upon word transition. Second, we plan to extend GTM to model deletions in sloppy speech, a major challenge in LVCSR.

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