Correcting errors in speech recognition with articulatory dynamics

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Abstract

We introduce a novel mechanism for incorporating articulatory dynamics into speech recognition with the theory of task dynamics. This system reranks sentence-level hypotheses by the likelihoods of their hypothetical articulatory realizations which are derived from relationships learned with aligned acoustic/articulatory data. Experiments compare this with two baseline systems, namely an acoustic hidden Markov model and a dynamic Bayes network augmented with discretized representations of the vocal tract. Our system based on task dynamics reduces word-error rates significantly by 10.2% relative to the best baseline models.

1 Introduction

Although modern automatic speech recognition (ASR) takes several cues from the biological perception of speech, it rarely models its biological production. The result is that speech is treated as a surface acoustic phenomenon with lexical or phonetic hidden dynamics but without any physical constraints in between. This omission leads to some untenable assumptions. For example, speech is often treated out of convenience as a sequence of discrete, non-overlapping packets, such as phonemes, despite the fact that some major difficulties in ASR, such as co-articulation, are by definition the result of concurrent physiological phenomena (Hardcastle and Hewlett, 1999).

Many acoustic ambiguities can be resolved with knowledge of the vocal tract's configuration (O'Shaughnessy, 2000). For example, the three nasal sonorants, */m/*, */n/*, and */ng/*, are acoustically similar (i.e., they have large concentrations of energy at the same frequencies) but uniquely and reliably involve bilabial closure, tongue-tip elevation, and tongue-dorsum elevation, respectively. Having access to the articulatory goals of the speaker would, in theory, make the identification of linguistic intent almost trivial. Although we don't typically have access to the vocal tract during speech recognition, its configuration *can* be estimated reasonably well from acoustics alone within adequate models or measurements of the vocal tract (Richmond et al., 2003; Toda et al., 2008). Evidence that such inversion takes place naturally in humans during speech perception suggests that the discriminability of speech sounds depends powerfully on their production (Liberman and Mattingly, 1985; D'Ausilio et al., 2009).

This paper describes the use of explicit models of physical speech production within recognition systems. Initially, we augment traditional models of ASR with probabilistic relationships between acoustics and articulation learned from appropriate data. This leads to the incorporation of a high-level, goal-oriented, and control-based theory of speech production within a novel ASR system.

2 Background and related work

The use of theoretical (phonological) features of the vocal tract has provided some improvement over traditional acoustic ASR systems in phoneme recognition with neural networks (Kirchhoff, 1999; Roweis, 1999), but there has been very little work in ASR informed by direct measurements of the vocal tract. Recently, Markov et al. (2006) have augmented hidden Markov models with Bayes networks trained to describe articulatory constraints from a small amount of Japanese vocal tract data, resulting in a small phoneme-error reduction. This work has since been expanded upon to inform ASR systems sensitive to physiological speech disorders (Rudzicz, 2009). Common among previous efforts is an interpretation of speech as a sequence of short, instantaneous observations devoid of long-term dynamics.

2.1 Articulatory phonology

Articulatory phonology bridges the divide between the physical manifestation of speech and its underlying lexical intentions. Within this discipline, the theory of *task dynamics* is a combined model of physical articulator motion and the planning of abstract vocal tract configurations (Saltzman, 1986). This theory introduces the notion that all observed patterns of speech are the result of overlapping *gestures*, which are abstracted goal-oriented reconfigurations of the vocal tract, such as bilabial closure or velar opening (Saltzman and Munhall, 1989). Each gesture occurs within one of the following *tract variables* (TVs): velar opening (**VEL**), lip aperture (**LA**) and protrusion (**LP**), tongue tip constriction location (**TTCL**) and degree (**TTCD**) [1], tongue body constriction location (**TBCL**) and degree (**TBCD**), lower tooth height (**LTH**), and glottal vibration (**GLO**). For example, the syllable *pub* consists of an onset (*/p/*), a nucleus (*/ah/*), and a coda (*/b/*). Four gestural goals are associated with the onset, namely the shutting of GLO and of VEL, and the closure and release of LA. Similarly, the nucleus of the syllable consists of three goals, namely the relocation of TBCD and TBCL, and the opening of GLO. The presence and extent of these gestural goals are represented by filled rectangles in figure 1. Inter-gestural timings between these goals are specified relative to one another according to human data as described by Nam and Saltzman (2003).

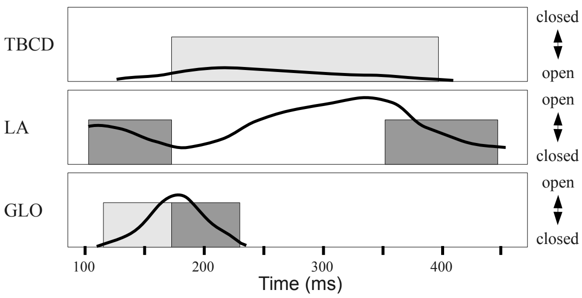


Figure 1: Canonical example *pub* from Saltzman and Munhall (1989).

The presence of these discrete goals influences the vocal tract dynamically and continuously as modelled by the following non-homogeneous second-order linear differential equation:

$$Mz'' + Bz' + K(z - z^*) = 0. \tag{1}$$

[1]Constriction *locations* generally refer to the front-back dimension of the vocal tract and constriction *degrees* generally refer to the top-down dimension.

Here, z is a continuous vector representing the instantaneous positions of the nine tract variables, z^* is the target (equilibrium) positions of those variables, and vectors z' and z'' represent the first and second derivatives of z with respect to time (i.e., velocity and acceleration), respectively. The matrices M, B, and K are syllable-specific coefficients describing the inertia, damping, and stiffness, respectively, of the virtual gestures. Generally, this theory assumes that the tract variables are mutually independent, and that the system is critically damped (i.e., the tract variables do not oscillate around their equilibrium positions) (Nam and Saltzman, 2003). The continuous state, z, of equation (1) is exemplified by black curves in figure 1.

2.2 Articulatory data

Tract variables provide the dimensions of an abstract gestural space independent of the physical characteristics of the speaker. In order to complete our articulatory model, however, we require physical data from which to infer these high-level articulatory goals.

Electromagnetic articulography (EMA) is a method to measure the motion of the vocal tract during speech. In EMA, the speaker is placed within a low-amplitude electromagnetic field produced within a cube of a known geometry. Tiny sensors within this field induce small electric currents whose energy allows the inference of articulator positions and velocities to within 1 mm of error (Yunusova et al., 2009). We derive data for the following study from two EMA sources:

- The University of Edinburgh's MOCHA database, which provides phonetically-balanced sentences repeated from TIMIT (Zue et al., 1989) uttered by a male and a female speaker (Wrench, 1999), and

- The University of Toronto's TORGO database, from which we select sentences repeated from TIMIT from two females and three males (Rudzicz et al., 2008). (Cerebrally palsied speech, which is the focus of this database, is not included here).

For the following study we use the eight 2D positions common to both databases, namely the upper lip (UL), lower lip (LL), upper incisor (UI), lower incisor (LI), tongue tip (TT), tongue blade (TB), and tongue dorsum (TD). Since these positions are recorded in 3D in TORGO, we project these onto the midsagittal plane. (Additionally, the MOCHA database provides velum (V) data on this plane, and TORGO provides the left and right lip corners (LL and RL) but these are excluded from study except where noted).

All articulatory data is aligned with its associated acoustic data, which is transformed to Mel-frequency cepstral coefficients (MFCCs). Since the 2D EMA system in MOCHA and the 3D EMA system in TORGO differ in their recording rates, the length of each MFCC frame in each database must differ in order to properly align acoustics with articulation in time. Therefore, each MFCC frame covers 16 ms in the TORGO database, and 32 ms in MOCHA. Phoneme boundaries are determined automatically in the MOCHA database by forced alignment, and by a speech-language pathologist in the TORGO database.

We approximate the tract variable space from the physical space of the articulators, in general, through principal component analysis (PCA) on the latter, and subsequent sigmoid normalization on $[0,1]$. For example, the LTH tract variable is inferred by calculating the first principal component of the two-dimensional lower incisor (LI) motion in the midsagittal plane, and by normalizing the resulting univariate data through a scaled sigmoid. The VEL variable is inferred similarly from velum (V) EMA data. Tongue tip constriction location and degree (TTCL and TTCD, respectively) are inferred from the 1^{st} and 2^{nd} principal components of tongue tip (TT) EMA data, with TBCL and TBCD inferred similarly from tongue body (TB) data. Finally, the glottis (GLO) is inferred by voicing detection on acoustic energy below 150 Hz (O'Shaughnessy, 2000), lip aperture (LA) is the normalized Euclidean distance between the lips, and lip protrusion (LP) is the normalized 2^{nd} principal component of the midpoint between the lips. All PCA is performed without segmentation of the data. The result is a low-dimensional set of continuous curves describing goal-relevant articulatory variables. Figure 2, for example, shows the degree of the lip aperture (LA) over time for all instances of the */b/* phoneme in the MOCHA database. The relevant articulatory goal of lip closure is evident.

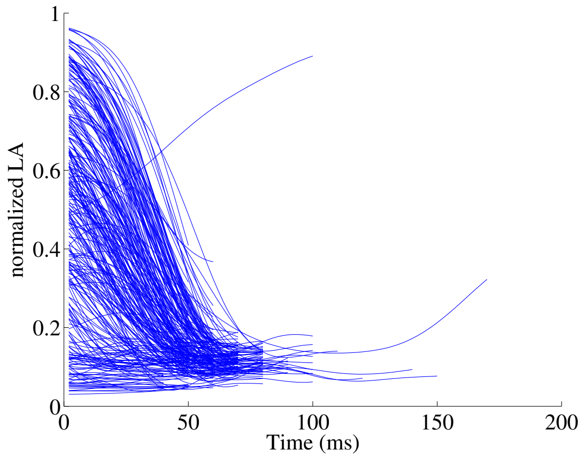


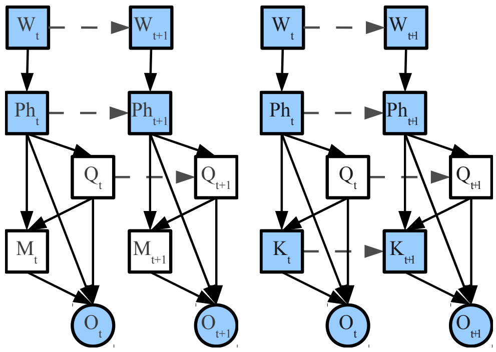
Figure 2: Lip aperture (LA) over time during all MOCHA instances of */b/*.

3 Baseline systems

We now turn to the task of speech recognition. Traditional Bayesian learning is restricted to universal or immutable relationships, and is agnostic towards dynamic systems or time-varying relationships. Dynamic Bayes networks (DBNs) are directed acyclic graphs that generalize the powerful stochastic mechanisms of Bayesian representation to temporal sequences. We are free to explicitly provide topological (i.e., dependency) relationships between relevant variables in our models, which can include measurements of tract data.

We examine two baseline systems. The first is the standard acoustic hidden Markov model (HMM) augmented with a bigram language model, as shown in figure 3(a). Here, $W_t \to W_{t+1}$ represents word transition probabilities, learned by maximum likelihood estimation, and $Ph_t \to Ph_{t+1}$ represents phoneme transition probabilities whose order is explicitly specified by the relationship $W_t \to Ph_t$. Likewise, each phoneme Ph conditions the sub-phoneme state, Q_t, whose transition probabilities $Q_t \to Q_{t+1}$ describe the dynamics within phonemes. The variable M_t refers to hidden Gaussian indices so that the likelihoods of acoustic observations, O_t, are represented by a mixture of 4, 8, 16, or 32 Gaussians for each state and each phoneme. See Murphy (2002) for a further description of this representation.

The second baseline model is the articulatory dynamic Bayes network (DBN-A). This augments the standard acoustic HMM by replacing hidden indices, M_t, with discrete observations of the vocal tract, K_t, as shown in figure 3(b). The pattern of acoustics within each phoneme is dependent on a relatively restricted set of possible articulatory configurations (Roweis, 1999). To find these discrete positions, we obtain k vectors that best describe the articulatory data according to k-means clustering with the sum-of-squares error function. During training, the DBN variable K_t is set explicitly to the *index* of the mean vector nearest to the current frame of EMA data at time t. In this way, the relationship $K_t \to O_t$ allows us to learn how discretized articulatory configurations affect acoustics. The training of DBNs involves a specialized version of expectation-maximization, as described in the literature (Murphy, 2002; Ghahramani, 1998). During inference, variables W_t, Ph_t, and K_t become hidden and we marginalize over their possible values when computing their likelihoods. Bigrams are computed by maximum likelihood on lexical annotations in the training data.



(a) HMM (b) DBN-A

Figure 3: Baseline systems: (a) acoustic hidden Markov model and (b) articulatory dynamic Bayes network. Node W_t represents the current word, Ph_t is the current phoneme, Q_t is that phoneme's dynamic state, O_t is the acoustic observation, M_t is the Gaussian mixture component, and K_t is the discretized articulatory configuration. Filled nodes represent observed variables during training, although only O_t is observed during recognition. Square nodes are discrete variables while circular nodes are continuous variables.

4 Switching Kalman filter

Our first experimental system attempts speech recognition given only articulatory data. The true state of the tract variables at time $t-1$ constitutes a 9-dimensional vector, $\mathbf{x}_{t-1}$, of continuous values. Under the task dynamics model of section 2.1, the motions of these tract variables obey critically damped second-order oscillatory relationships. We start with the simplifying assumption of linear dynamics here with allowances for random Gaussian *process noise*, $\mathbf{v}_t$, since articulatory behaviour is non-deterministic. Moreover, we know that EMA recordings are subject to some error (usually less than 1 mm (Yunusova et al., 2009)), so the actual observation at time t, $\mathbf{y}_t$, will not in general be the true position of the articulators. Assuming that the relationship between $\mathbf{y}_t$ and $\mathbf{x}_t$ is also linear, and that the *measurement noise*, $\mathbf{w}_t$, is also Gaussian, then the dynamical articulatory system can be described by

$$\begin{aligned} \mathbf{x}_t &= D_t \mathbf{x}_{t-1} + \mathbf{v}_t \\ \mathbf{y}_t &= C_t \mathbf{x}_t + \mathbf{w}_t. \end{aligned} \tag{2}$$

Eqs. 2 form the basis of the Kalman filter which allows us to use EMA measurements directly, rather than quantized abstractions thereof as in the DBN-A model. Obviously, since articulatory dynamics vary significantly for different goals, we replicate eq. (2) for each phoneme and connect these continuous Kalman filters together with discrete conditioning variables for phoneme and word, resulting in the switching Kalman filter (SKF) model. Here, parameters D_t and $\mathbf{v}_t$ are implicit in the relationship $\mathbf{x}_t \to \mathbf{x}_{t+1}$, and parameters C_t and $\mathbf{w}_t$ are implicit in $\mathbf{x}_t \to \mathbf{y}_t$. In this model, observation $\mathbf{y}_t$ is the instantaneous measurements derived from EMA, and $\mathbf{x}_t$ is their true hidden states. These parameters are trained using expectation-maximization, as described in the literature (Murphy, 1998; Deng et al., 2005).

5 Recognition with task dynamics

Our goal is to integrate task dynamics within an ASR system for continuous sentences called TD-ASR. Our approach is to re-rank an N-best list of sentence hypotheses according to a weighted likelihood of their articulatory realizations. For example, if a word sequence $W_i : w_{i,1}\ w_{i,2}\ \ldots\ w_{i,m}$ has likelihoods $L_X(W_i)$ and $L_\Lambda(W_i)$ according to purely acoustic and articulatory interpretations of an utterance, respectively, then its overall score would be

$$L(W_i) = \alpha L_X(W_i) + (1-\alpha) L_\Lambda(W_i) \tag{3}$$

given a weighting parameter α set manually, as in section 6.2. Acoustic likelihoods $L_X(W_i)$ are obtained from Viterbi paths through relevant HMMs in the standard fashion.

5.1 The TADA component

In order to obtain articulatory likelihoods, $L_\Lambda(W_i)$, for each word sequence, we first generate articulatory realizations of those sequences according to task dynamics. To this end, we use components from the open-source `TADA` system (Nam and Goldstein, 2006), which is a complete implementation of task dynamics. From this toolbox, we use the following components:

- A syllabic dictionary supplemented with the International Speech Lexicon Dictionary (Hasegawa-Johnson and Fleck, 2007). This breaks word sequences W_i into syllable sequences S_i consisting of onsets, nuclei, and coda and covers all of MOCHA and TORGO.
- A syllable-to-gesture lookup table. Given a syllabic sequence, S_i, this table provides the gestural goals necessary to produce those syllables. For example, given the syllable *pub* in figure 1, this table provides the targets for the GLO, VEL, TBCL, and TBCD tract variables, and the parameters for the second-order differential equation, eq. 1, that achieves those goals. These parameters have been empirically tuned by the authors of `TADA` according to a generic, speaker-independent representation of the vocal tract (Saltzman and Munhall, 1989).
- A component that produces the continuous tract variable paths that produce an utterance. This component takes into account various physiological aspects of human speech production, including intergestural and interarticulator co-ordination and timing (Nam and Saltzman, 2003; Goldstein and Fowler, 2003), and the neutral ("schwa") forces of the vocal tract (Saltzman and Munhall, 1989). This component takes a sequence of gestural goals predicted by the segment-to-gesture lookup table, and produces appropriate paths for each tract variable.

The result of the `TADA` component is a set of N 9-dimensional articulatory paths, $\mathbf{TV}_i$, necessary to produce the associated word sequences, W_i for $i = 1..N$. Since task dynamics is a prescriptive model and fully deterministic, $\mathbf{TV}_i$ sequences are the *canonical* or default articulatory realizations of the associated sentences. These canonical realizations are independent of our training data, so we transform them in order to more closely resemble the observed articulatory behaviour in our EMA data. Towards this end, we train a switching Kalman filter identical to that in section 4, except the hidden state variable $\mathbf{x}_t$ is replaced by the observed instantaneous *canonical* TVs predicted by `TADA`. In this way we are explicitly learning a relationship between `TADA`'s task dynamics and human data. Since the lengths of these sequences are generally unequal, we align the articulatory behaviour predicted by `TADA` with training data from MOCHA and TORGO using standard dynamic time warping (Sakoe and Chiba, 1978). During run-time, the articulatory sequence $\mathbf{y}_t$ most likely to have been produced by the human data given the canonical sequence $\mathbf{TV}_i$ is inferred by the Viterbi algorithm through the SKF model with all other variables hidden. The result is a set of articulatory sequences, $\mathbf{TV}_i^*$, for $i = 1..N$, that represent the predictions of task dynamics that better resemble our data.

5.2 Acoustic-articulatory inversion

In order to estimate the articulatory likelihood of an utterance, we need to evaluate each transformed articulatory sequence, $\mathbf{TV}_i^*$, within probability distributions ranging over all tract variables. These distributions can be inferred using acoustic-articulatory inversion. There are a number of approaches to this task, including vector quantization, and expectation-maximization with Gaussian mixtures (Hogden and Valdez, 2001; Toda et al., 2008). These approaches accurately inferred the *xy* position of articulators to within 0.41 mm and 2.73 mm. Here, we modify the approach taken by Richmond et al. (2003), who estimate probability functions over the 2D midsagittal positions of 7 articulators, given acoustics, with a mixture-density network (MDN). An MDN is essentially a typical discriminative multi-layer neural network whose output consists of the parameters to Gaussian mixtures. Here, each Gaussian mixture describes a probability function over TV positions given the acoustic frame at time t. For example, figure 4 shows an intensity map of the likely values for tongue-tip constriction degree (TTCD) for each frame of acoustics, superimposed with the 'true' trajectory of that TV. Our networks are trained with acoustic and EMA-derived data as described in section 2.2.

5.3 Recognition by reranking

During recognition of a test utterance, a standard acoustic HMM produces word sequence hypotheses, W_i, and associated likelihoods, $L(W_i)$, for $i = 1..N$. The expected canonical motion of the tract variables, $\mathbf{TV}_i$ is then produced by task dynamics

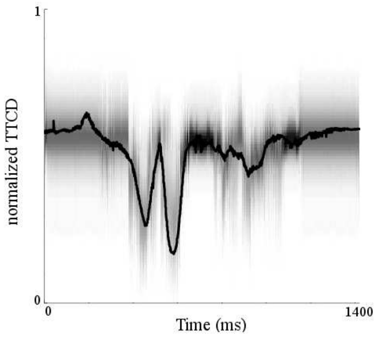


Figure 4: Example probability density of tongue tip constriction degree over time, inferred from acoustics. The true trajectory is superimposed as a black curve.

for each of these word sequences and transformed by an SKF to better match speaker data, giving $\mathbf{TV}_i^*$. The likelihoods of these paths are then evaluated within probability distributions produced by an MDN. The mechanism for producing the articulatory likelihood is shown in figure 5. The overall likelihood, $L(W_i) = \alpha L_X(W_i) + (1-\alpha)L_\Lambda(W_i)$, is then used to produce a final hypothesis list for the given acoustic input.

6 Experiments

Experimental data is obtained from two sources, as described in section 2.2. We procure 1200 sentences from Toronto's TORGO database, and 896 from Edinburgh's MOCHA. In total, there are 460 total unique sentence forms, 1092 total unique word forms, and 11065 total words uttered. Except where noted, all experiments randomly split the data into 90% training and 10% testing sets for 5-cross validation. MOCHA and TORGO data are never combined in a single training set due to differing EMA recording rates. In all cases, models are database-dependent (i.e., all TORGO data is conflated, as is all of MOCHA).

For each of our baseline systems, we calculate the phoneme-error-rate (PER) and word-error-rate (WER) after training. The phoneme-error-rate is calculated according to the proportion of frames of speech incorrectly assigned to the proper phoneme. The word-error-rate is calculated as the sum of insertion, deletion, and substitution errors in the highest-ranked hypothesis divided by the total number of words in the correct orthography. The traditional HMM is compared by varying the number of Gaussians used in the modelling

System	Parameters	PER (%)	WER (%)
HMM	$\|M\| = 4$	29.3	14.5
	$\|M\| = 8$	27.0	13.9
	$\|M\| = 16$	26.1	10.2
	$\|M\| = 32$	25.6	9.7
DBN-A	$\|K\| = 4$	26.1	13.0
	$\|K\| = 8$	25.2	11.3
	$\|K\| = 16$	24.9	9.8
	$\|K\| = 32$	24.8	9.4

Table 1: Phoneme- and Word-Error-Rate (PER and WER) for different parameterizations of the baseline systems.

	No. of Gaussians			
	1	2	3	4
LTH	−0.28	−0.18	−0.15	−0.11
LA	−0.36	−0.32	−0.30	−0.29
LP	−0.46	−0.44	−0.43	−0.43
GLO	−1.48	−1.30	−1.29	−1.25
TTCD	−1.79	−1.60	−1.51	−1.47
TTCL	−1.81	−1.62	−1.53	−1.49
TBCD	−0.88	−0.79	−0.75	−0.72
TDCL	−0.22	−0.20	−0.18	−0.17

Table 2: Average log likelihood of true tract variable positions in test data, under distributions produced by mixture density networks with varying numbers of Gaussians.

of acoustic observations. Similarly, the DBN-A model is compared by varying the number of discrete quantizations of articulatory configurations, as described in section 3. Results are obtained by direct decoding. The average results across both databases, between which there are no significant differences, are shown in table 1. In all cases the DBN-A model outperforms the HMM, which highlights the benefit of explicitly conditioning acoustic observations on articulatory causes.

6.1 Efficacy of TD-ASR components

In order to evaluate the whole system, we start by evaluating its parts. First, we test how accurately the mixture-density network (MDN) estimates the position of the articulators given only information from the acoustics available during recognition. Table 2 shows the average log likelihood over each tract variable across both databases. These results are consistent with the state-of-the-art (Toda et al., 2008). In the following experiments, we use MDNs that produce 4 Gaussians.

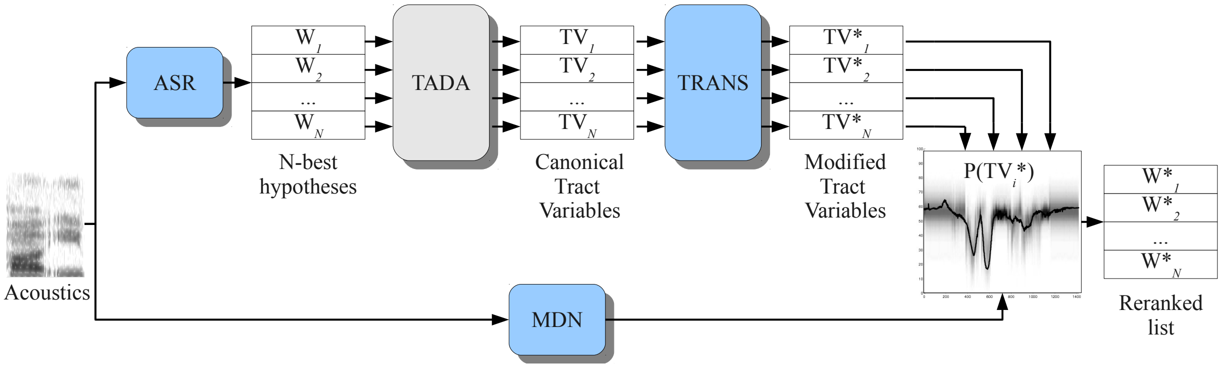


Figure 5: The TD-ASR mechanism for deriving articulatory likelihoods, $L_\Lambda(W_i)$, for each word sequence W_i produced by standard acoustic techniques.

Manner	Canonical	Transformed
approximant	0.19	0.16
fricative	0.37	0.29
nasal*	0.24	0.18
retroflex	0.23	0.19
plosive	0.10	0.08
vowel	0.27	0.25

Table 3: Average difference between predicted tract variables and observed data, on $[0,1]$ scale. (*) Nasals are evaluated only with MOCHA data, since TORGO data lacks velum measurements.

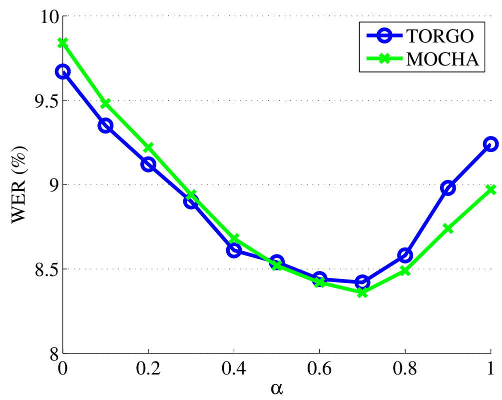


Figure 6: Word-error-rate according to varying α, for both TORGO and MOCHA data.

We evaluate how closely transformations to the canonical tract variables predicted by TADA match the data. Namely, we input the known orthography for each test utterance into TADA, obtain the predicted canonical tract variables **TV**, and transform these according to our trained SKF. The resulting predicted and transformed sequences are aligned with our measurements derived from EMA with dynamic time warping. Finally, we measure the average difference between the observed data and the predicted (canonical and transformed) tract variables. Table 3 shows these differences according to the phonological manner of articulation. In all cases the transformed tract variable motion is more accurate, and significantly so at the 95% confidence level for nasal and retroflex phonemes, and at 99% for fricatives. The practical utility of the transformation component is evaluated in its effect on recognition rates, as described below.

6.2 Recognition with TD-ASR

With the performance of the components of TD-ASR better understood, we combine these and study the resulting composite TD-ASR system.

Figure 6 shows the WER as a function of α with TD-ASR and $N = 4$ hypotheses per utterance. The effect of α is clearly non-monotonic, with articulatory information clearly proving useful. Although systems whose rankings are weighted solely by the articulatory component perform better than the exclusively acoustic systems, the lists available to the former are procured from standard acoustic ASR. Interestingly, the gap between systems trained to the two databases increases as α approaches 1.0. Although this gap is not significant, it may be the result of increased inter-speaker articulatory variation in the TORGO database, which includes more than twice as many speakers as MOCHA.

Figure 7 shows the WER obtained with TD-ASR given varying-length N-best lists and $\alpha = 0.7$. TD-ASR accuracy at $N = 4$ is significantly better than both TD-ASR at $N = 2$ and the baseline approaches of table 1 at the 95% confidence level. However, for $N > 4$ there is a noticeable and systematic worsening of performance.

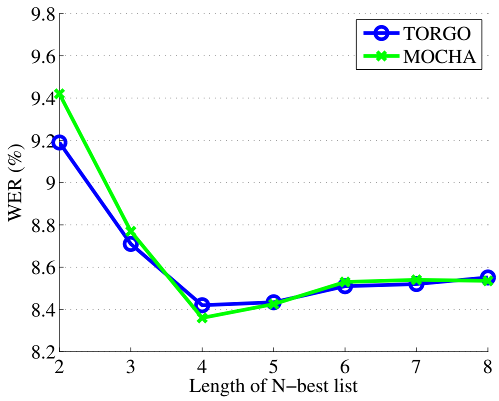


Figure 7: Word-error-rate according to varying lengths of *N*-best hypotheses used, for both TORGO and MOCHA data.

The optimal parameterization of the TD-ASR model results in an average word-error-rate of 8.43%, which represents a 10.3% relative error reduction over the best parameterization of our baseline models. The SKF model of section 4 differs from the HMM and DBN-A baseline models only in its use of continuous (rather than discrete) hidden dynamics and in its articulatory observations. However, its performance is far more variable, and less conclusive. On the MOCHA database the SKF model had an average of 9.54% WER with a standard deviation of 0.73 over 5 trials, and an average of 9.04% WER with a standard deviation of 0.64 over 5 trials on the TORGO database. Despite the presupposed utility of direct articulatory observations, the SKF system does not perform significantly better than the best DBN-A model.

Finally, the experiments of tables 6 and 7 are repeated with the canonical tract variables passed untransformed to the probability maps generated by the MDNs. Predictably, resulting articulatory likelihoods L_Λ are less representative and increasing their contribution α to the hypothesis reranking does not improve TD-ASR performance significantly, and in some instances worsens it. Although `TADA` is a useful prescriptive model of generic articulation, its use must be tempered with knowledge of inter-speaker variability.

7 Discussion and conclusions

The articulatory medium of speech rarely informs modern speech recognition. We have demonstrated that the use of direct articulatory knowledge can substantially reduce phoneme and word errors in speech recognition, especially if that knowledge is motivated by high-level abstractions of vocal tract behaviour. Task dynamic theory provides a coherent and biologically plausible model of speech production with consequences for phonology (Browman and Goldstein, 1986), neurolinguistics (Guenther and Perkell, 2004), and the evolution of speech and language (Goldstein et al., 2006). We have shown that it is also useful within speech recognition.

We have overcome a conceptual impediment in integrating task dynamics and ASR, which is the former's deterministic nature. This integration is accomplished by stochastically transforming predicted articulatory dynamics and by calculating the likelihoods of these dynamics according to speaker data. However, there are several new avenues for exploration. For example, task dynamics lends itself to more general applications of control theory, including automated self-correction, rhythm, co-ordination, and segmentation (Friedland, 2005). Other high-level questions also remain, such as whether discrete gestures are the correct biological and practical paradigm, whether a purely continuous representation would be more appropriate, and whether this approach generalizes to other languages.

In general, our experiments have revealed very little difference between the use of MOCHA and TORGO EMA data. An *ad hoc* analysis of some of the errors produced by the TD-ASR system found no particular difference between how systems trained to each of these databases recognized nasal phonemes, although only those trained with MOCHA considered velum motion. Other errors common to both sources of data include phoneme insertion errors, normally vowels, which appear to co-occur with some spurious motion of the tongue between segments, especially for longer *N*-best lists. Despite the relative slow motion of the articulators relative to acoustics, there remains some intermittent noise.

As more articulatory data becomes available and as theories of speech production become more refined, we expect that their combined value to speech recognition will become indispensable.

Acknowledgments

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