**FACTS: A hierarchical task-based control model of speech incorporating sensory feedback**

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**Abstract**

We present a computational model of speech motor control that integrates vocal tract state prediction with sensory feedback. This hierarchical model, called FACTS, incorporates both a high-level and low-level controller. The high-level controller orchestrates linguistically-relevant speech tasks, which are represented as desired constrictions along the vocal tract (e.g., closure of the lips). The output of the high-level controller is passed to a low-level controller that can issue motor commands at the level of the speech articulators in order to accomplish the desired constrictions. In order to generate these articulatory motor commands, the low-level articulatory controller relies on an estimate of the current state of the vocal tract. This estimate combines internal predictions about the consequences of issued motor commands with auditory and somatosensory feedback from the vocal tract using an Unscented Kalman Filter based state estimation method. FACTS is able to reproduce several important aspects of human speech behavior such as: (i) stable speech behavior in the presence of noisy motor and sensory systems, (ii) partial acoustic compensation to auditory feedback perturbations, (iii) complete compensations to mechanical perturbations only when they interfere with current production goals, and (iv) the observed relationship between sensory acuity and response to sensory perturbations.

**Index Terms:** speech motor control, auditory feedback, task dynamics, state feedback control, feedback perturbation, speech production, speech modeling

1. Feedback and Speech Motor Control

Sensory feedback is important for speech motor control. Multiple research studies have shown that speakers compensate for perturbations to auditory and/or somatosensory feedback [1, 2], and that delayed auditory feedback disrupts the production of fluent speech [3, 4]. However, one intriguing aspect of the speech production process is that while it is responsive to auditory and somatosensory feedback, it is not critically dependent on it. We know this because post-lingually deafened adults can produce intelligible speech [5]. In addition, speech is highly intelligible during oral sensory and auditory deprivation, even though articulatory precision is affected [6]. Models of speech motor control therefore need to account for the effects of sensory feedback on the articulation process, without critically relying on it.

A number of speech motor control models have been proposed in recent years, including (among others) the DIVA model [7], Task Dynamics [8], and State Feedback Control or SFC [9]. While both SFC and Task Dynamics have evolved out of a general feedback controller, Task Dynamics has at its heart a controller that generates state-dependent motor commands that drive changes in the speech articulators [8, 10], while assuming that the instantaneous state of the speech production system can be known without error. SFC models how the CNS can estimate the state of the speech production system from noisy, delayed feedback signals [11] using optimal control principles [12], but does not model how that state can be used by the controller to generate motor commands. More recently, we proposed a novel speech production model – TD-SFC [13] – that overcomes the individual disadvantages of each model by composing a neurobiologically inspired short-latency feedback control scheme (derived from State Feedback Control) with the well-developed method for deriving utterance-specific control laws and generating the resulting articulatory and acoustic outcomes (derived from Task Dynamics).

In this paper, we present a more robust and updated version of that model, which we dub FACTS (Feedback-Aware Control of Tasks in Speech). We show that the FACTS model can reproduce several important aspects of human speech behavior.

2. Modeling

2.1. Task Dynamics Modeling Preliminaries

The Task Dynamics Application (or TaDA) model [14, 15, 10] implements the Task Dynamic model of inter-articulator speech coordination with the framework of Articulatory Phonology [16]. Based on any arbitrary orthographic (ARPABET) input, TaDA uses a feedback control schema to control a configurable articulatory speech synthesizer [17, 18], generating both articulatory and acoustic output. In TaDA, articulatory control and functional coordination of the speech articulators is accomplished with reference to speech ‘tasks’ which are coordinated together in time. Speech tasks, or ‘gestures’, are taken to be constriction actions of the vocal tract (e.g., close the lips), with specific spatial targets and temporal extents. Each gesture controls multiple speech articulators that are used coordinately to achieve that particular task (e.g., the upper lip, low lip, and jaw move together to close the lips) [16]. Each gesture is modeled as a point attractor with second-order mass-spring dynamics, which when active forms part of the multi-dimensional control law that governs how the vocal tract changes through time. This time-varying control law, unique to each utterance, is known as a gestural score.

We gratefully acknowledge the support of NIH Grants R01DC013979, R01DC010145, R01NS100440 and F32DC014211 and NSF Grant BCS1262297.
Vocal Tract State Estimate

Constriction task of constriction task variables the state of the vocal tract tasks from time-varying articulatory trajectories. Here we represent the command from the controller and produces changes in the current Task Dynamics model [8]. This model contains 1) a level articulators (or, at a level not modeled here, muscles or motor neurons). As such, TaDA generates changes in the positions of the organs of the model vocal tract (articulatory variables, a) which can be nonlinearly related to the task variables using the so-called ‘direct kinematics’ relationship.

2.2. FACTS model

This section extends an earlier version of a task-based state feedback control model [13], TD-SFC (Task Dynamics-State Feedback Control). A schematic control diagram of our current model is shown in Figure 1. The dashed blue boxes replicate the current Task Dynamics model [8]. This model contains 1) a controller, 2) a model vocal tract or plant that receives a motor command from the controller and produces changes in the articulatory state, and 3) a model to generate acoustic output from time-varying articulatory trajectories. Here we represent the state of the vocal tract tasks \( x_t = [x_t, \dot{x}_t]^T \) at time \( t \) by a set of constriction task variables \( x_t \) and their velocities \( \dot{x}_t \). Given a gestural score generated using a linguistic gestural model as described earlier, the Forward Task Dynamics model allows us to compute the state derivative \( \dot{x}_t \) as follows:

\[
\dot{x}_t = \begin{bmatrix} \frac{1}{\text{c}} & 0 \\ -\frac{1}{\text{c}^2} \end{bmatrix} x_t + \begin{bmatrix} 0 \\ \text{c} \end{bmatrix} \dot{x}_t
\]

(1)

where \( x \) refers to the task variable (or goal variable) vector, which is defined in TaDA as a set of constriction degrees (such as lip aperture, tongue tip constriction degree, velic aperture, etc.) or locations (such as tongue tip constriction location). \( M \) is the mass matrix, \( B \) is the damping coefficient matrix, \( K \) is the stiffness coefficient matrix of the second-order dynamical system model, and \( c \) is a constant.

Next we use Equation 2 (after [8]) to perform an inverse kinematics mapping from the task accelerations \( \ddot{x}_t \) to the model articulator accelerations \( \ddot{a}_t \), a process which is also dependent on the current estimate of the articulator positions \( \hat{a}_t \) and velocities \( \dot{a}_t \). \( J \) is the Jacobian matrix of the forward kinematics model relating articulatory states to task states.

\[
x = J(a)
\]

(2a)

\[
\dot{x} = J(a)\dot{a}
\]

(2b)

Euler integration allows us to compute the model articulator positions and velocities for the next time-step, which effectively “moves” the articulatory vocal tract model. Then, an appropriate synthesis model converts the model articulator and constriction task values into output acoustic parameters \( y_t \).

While Task Dynamics assumes perfect observability and feedback of the current vocal tract state at every iteration of the model (represented by the dotted blue arrow in Figure 1), which is unrealistic for the human CNS given the variety of reasons discussed above. We implement a state-estimation procedure (Section 2.3, below), to estimate the articulatory state from an efference copy of the motor commands issued to the plant and sensory feedback.

This articulatory state estimate is passed back to the articulatory feedback controller and used to estimate the current state of the speech tasks \( \hat{s}_t \). This task state estimate is calculated by running the forward kinematics model \( f \) (see Equation 2) based on the estimate of articulatory state \( \hat{a}_t \), and the output of this process is passed to the task feedback controller.

2.3. State estimation

The basic concept of SFC is that a copy of the motor command ('efference copy') is passed to an internal model of the vocal tract. Based on this efference copy, the internal model generates 1) an estimate of the next state of the speech articulators and 2) an estimate of the sensory consequences of the estimated state.

In FACTS, this forward modeling of articulatory state and sensory consequences is accomplished through an Unscented Kalman Filter (UKF) [19]. The UKF is an extension of the principles of the Kalman Filter to nonlinear systems that has been shown to be more stable and accurate than the method we previously employed [13], the Extended Kalman Filter [20]. In order to generate a posterior mean and covariance, the EKF approximates a non-linear transformation function and projects a single prior through that linearized function. However, the approximations in this process can sometimes lead to sub-optimal performance. In a UKF, multiple prior points (called sigma points, \( \chi \)) are used. These prior points are chosen carefully to capture the mean and covariance of the prior state. Each of these points is then projected through the true un-transformed non-linear function, after which the posterior mean and covariance can be calculated from the transformed points. This process is called the unscented transform. This is used both to predict the future state of the system (process model) as well as the expected sensory feedback (observation model). The means and covariances calculated through these unscented transforms are then used analogously to their use in a standard Kalman Filter to estimate the optimal posterior state.

In our model, the output of the inverse kinematics model (\( \hat{a}_t \), which is equivalent to the motor command) is passed to the observer/UKF. This is combined with an estimate of the current articulatory state \( \hat{a}_{t-1} = [\hat{a}_{t-1} \, \hat{\dot{a}}_{t-1}]^T \) to generate an articulatory state prediction. First, the sigma points (\( \chi \)) are generated:

\[
\chi_{t-1} = [\hat{s}_{t-1} \pm \sqrt{L + \lambda}\bar{P}_{t-1}] \quad (3)
\]

where \( \hat{s}_{t-1} = [\hat{a}_{t-1} \, \hat{\dot{a}}_{t-1} \, \hat{\ddot{a}}_{t-1}]^T \), and \( \nu \) and \( \nu \) are the process and observation noise, respectively. \( L \) is the dimension of the dimension of the articulatory state \( \alpha \), \( \lambda \) is a scaling factor, and \( \bar{P} \) is the noise covariance of \( \alpha, \nu \), and \( \nu \).

The observer then estimates how the motor command \( \hat{a}_t \) would effect the speech articulators by replicating using the
Euler integration model \((\mathcal{F})\) to generate the state prediction \(\hat{\mathbf{a}}_t = [\hat{a}_t \ 1\hat{a}_t]^T\). First, all sigma points reflecting the articulatory state \(X^n\) and process noise \(\mathbf{v}\) are passed through \(\mathcal{F}\):\footnote{Gaussians corresponding to the mean and variance of all LWPR receptive fields (below a certain variance threshold) to illustrate how LWPR models different regions of the CL space.}

\[
X^n_{t|t-1} = \mathcal{F}[X^n_{t-1}, \hat{\mathbf{a}}_{t-1}, \mathbf{v}_{t-1}]
\]

and the estimated articulatory state is calculated as the weighted sum of the sigma points where the weights \((W)\) are inversely related to the distance of the sigma point from the center of the distribution.

\[
\hat{\mathbf{a}}_t = \sum_{i=0}^{2L} W_i \ X^n_{i,t|t-1}
\]

The expected sensory state \((\hat{y}_t)\) is then derived based on the predicted articulatory state in a similar manner, first by projecting the articulatory \(X^n\) and observation noise \(X^o\) sigma points through the articulatory-to-sensory transform \(\mathcal{H}\).

\[
y^o_{i,t|t-1} = \mathcal{H}(X^n_{i,t|t-1}, X^o_{t-1})
\]

\[
\hat{y}_t = \sum_{i=0}^{2L} W_i \ y^o_{i,t|t-1}
\]

In the current version of the model, the sensory state \((\hat{y}_t)\) includes both auditory feedback \((y^a_{t|t})\) as well as somatosensory feedback \((y^s_{t|t})\), which have been shown to play a role in informing the state of the system [21]. Acoustic feedback is implemented as the values, in Hz, of the first three vowel formants (F1-F3). Somatosensory feedback is implemented as the positions and the velocities of the oral articulators in the CASY synthesizer.

This estimate of the sensory state is then compared against incoming sensory feedback \((y_t)\) to adjust the predicted articulatory state. To model sensory noise, Gaussian white noise \((\omega)\) is added to the formant values and articulator positions and velocities produced by the CASY with separate standard deviations for auditory and somatosensory signals. The updated state estimate \(\hat{\mathbf{a}}_t\) in this case is given by:

\[
\hat{\mathbf{a}}_t = \hat{\mathbf{a}}_t + \mathcal{K}_i(y_t - \hat{y}_t)
\]

where \(\Delta y = y_t - \hat{y}_t\) is the sensory error and \(\mathcal{K}_i\) is the Kalman Gain, which is computed as a function of the posterior covariance matrices \(P_{\mathbf{a}_t|y_t}\) and \(P_{\mathbf{y}_t|\mathbf{y}_t}\) in the following manner:

\[
\mathcal{K}_i = P_{\mathbf{a}_t|y_t} \mathcal{H}^T \left( P_{\mathbf{y}_t|\mathbf{y}_t} + \mathcal{H} P_{\mathbf{y}_t|y_t} \mathcal{H}^T \right)^{-1}
\]

\[
P_{\mathbf{a}_t|y_t} = \sum_{i=0}^{2L} W_i [\mathbf{a}_{i,t|t-1} - \hat{\mathbf{a}}_t][\mathbf{a}_{i,t|t-1} - \hat{\mathbf{a}}_t]^T
\]

\[
P_{\mathbf{y}_t|\mathbf{y}_t} = \sum_{i=0}^{2L} W_i [\mathbf{y}_{i,t|t-1} - \hat{\mathbf{y}}_t][\mathbf{y}_{i,t|t-1} - \hat{\mathbf{y}}_t]^T
\]

One of the challenges in implementing such an UKF is that both the process model \(\mathcal{F}\) (that provides a functional mapping from \([\hat{a}_{t-1} \ \hat{a}_{t-1} \ \hat{a}_{t-1}]^T\) to \(\hat{\mathbf{a}}_t\)) as well as the observation model \(\mathcal{H}\) (that maps from \(\mathbf{a}_t\) to \(\mathbf{y}_t\)) are unknown. Currently, we implement the process model \(\mathcal{F}\) by replicating the Euler integration equations used to drive changes in the CASY model.

Implementing the observation model is more challenging due to the nonlinear relationship between articulator positions and formant values. In order to solve this problem, we learn the observation model functional mappings from articulatory positions to acoustics \((y^a_{t|t|} = \mathcal{H}(\hat{\mathbf{a}}_t))\) required for Unscented Kalman Filtering using Locally Weighted Projection Regression, or LWPR, a computationally efficient machine learning technique [22]. While we do not here explicitly relate this machine learning process to human learning, such maps could theoretically be learned during early speech acquisition, such as babbling [7]. Currently, we learn only the auditory prediction component of \(\mathcal{H}\). Since the dimensions of the somatosensory prediction are identical to those of the predicted articulatory state, the former are generated from the latter via an identity function \((y^s_{t|t} = \hat{\mathbf{a}}_t)\).
While the speech motor system can operate independently of sensory feedback, there is strong evidence that the system does use acoustic feedback, when available, to control ongoing speech production [24, 25, 26]. When subjects’ speech forms are perturbed they compensate by shifting their own forms in the opposite direction (e.g. a positive shift in F1 played back to the subject induces a negative F1 shift in the subject’s production). In order to evaluate the ability of the FACTS model to reproduce this compensatory response to auditory perturbations, we simulated a simple altered auditory feedback experiment: we perturbed F1 of the vocal tract acoustic output \( y_{\text{ac}} \) by 100 Hz while the model was producing [5].

Figure 4 shows the results of one example simulation run of the FACTS model under F1 perturbation. The model initially starts with veridical (though noisy) feedback. At the onset of the shaded region, the perturbation is turned on. This causes a discrepancy between the perceived auditory feedback and the auditory predictions generated by the UKF. In response to this feedback error, the produced F1 lowers below the baseline value of 520 Hz, though not enough to fully compensate for the 100 Hz perturbation. This partial compensation qualitatively replicates human behavior in previous studies on altered auditory feedback perturbations. Critically, FACTS is able to replicate the compensatory behavior seen in response to auditory perturbations despite the absence of any explicit auditory goals in the model.

3.3. Consequences of sensory acuity

While the simulations in Section 3.1 showed that FACTS is stable in the presence of noise, the amount of noise in the sensory input does influence model behavior. Specifically, more noise for a given sensory channel results in a smaller weight in the Kalman gain for that channel. This can be seen when an +100 Hz perturbation is applied to the auditory feedback in the model.

Figure 5: Four simulation run of the FACTS model with altered auditory feedback and varying sensory noise. A perturbation of +100 Hz is applied to F1 during the shaded time period. A larger response is produced when auditory noise is low or when somatonsensory noise is high.

Figure 6: Simulation run of the FACTS model with a mechanical perturbation applied to the jaw. (Figure 5). More noise results in a smaller compensatory response. This simulation result mirrors behavioral findings that speakers who produce smaller compensatory responses to auditory perturbations have less acute auditory systems [27]. The opposite change is observed when somatonsensory noise is manipulated: a lower somatonsensory noise results in a smaller compensatory response. This suggests a trading relationship between auditory and somatonsensory acuity, consistent with a similar trade-off in auditory vs somatonsensory compensation in human behavior [28].

3.4. Responses to mechanical perturbations

When mechanical perturbations are applied to the jaw during a consonant closure, other articulators move to compensate for the lowered jaw position. The response of these articulators depends on the current production goal [29]. For example, the upper lip will lower in response to a jaw perturbation during /p/ but not /t/ [30]. We replicated these experiments by applying a downward force to the model jaw. FACTS qualitatively replicates human behavior, as seen in Figure 6. The upper and lower lip move to a compensate for the lower jaw only when needed to produce a bilabial /p/ (left), but not when producing a coronal /t/ (right).

4. Summary

We have elaborated the computational architecture of a new model of speech production, FACTS. We have shown that this model, though still under development, is capable of producing speech in the presence of sensory noise or even complete absence of sensory feedback, yet is able to use sensory information to correct for auditory and mechanical perturbations, producing corrective responses that qualitatively match human behavior.
5. References


