Simulating adaptation in the FACTS model of speech motor control: current progress, problems, and potential paths forward

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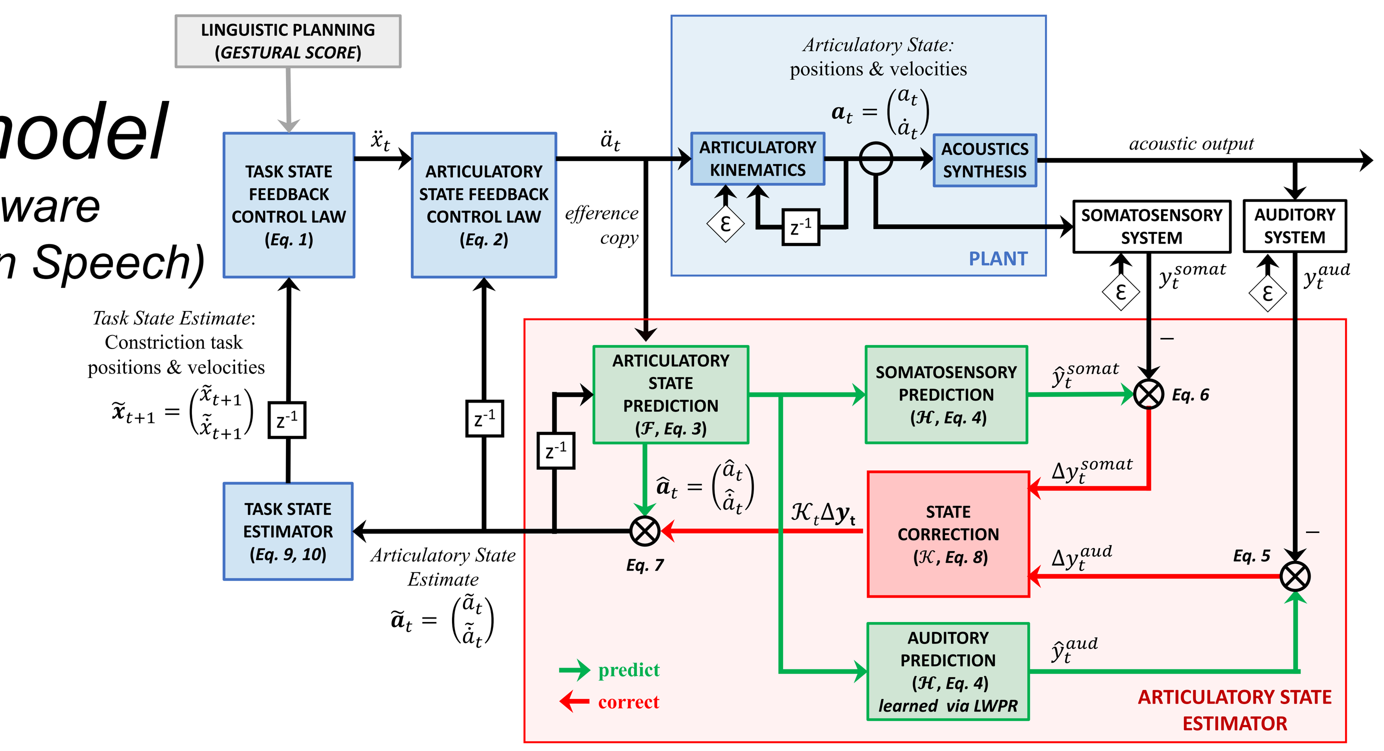
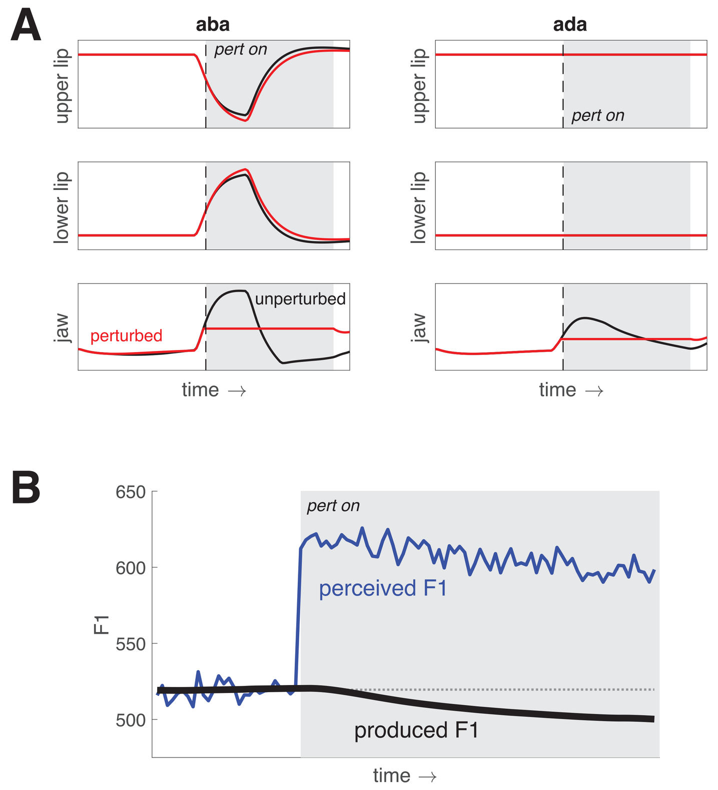
Background

FACTS model

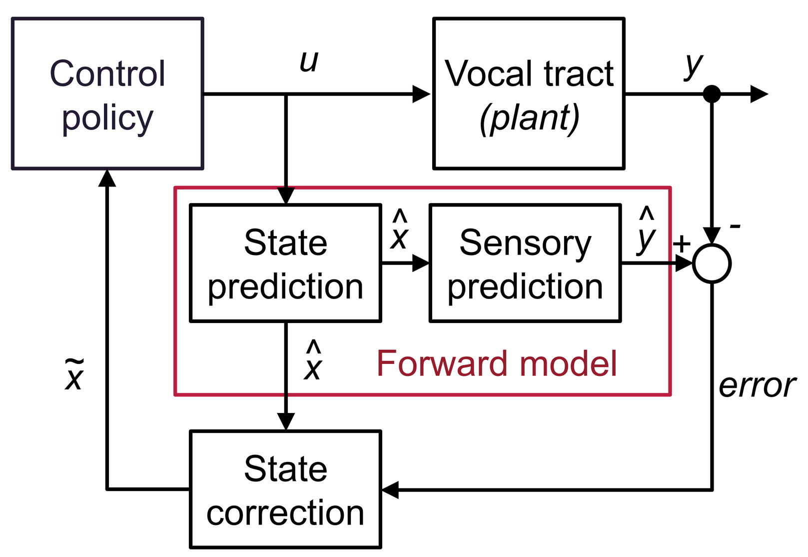
(Feedback Aware Control of Tasks in Speech)





- FACTS is a hierarchical control model which links the control of high-level speech tasks with lower-level control of speech articulation.
- FACTS builds on previous task- and feedback-based controllers (Task Dynamics, SFC).
- FACTS is able to replicate online responses to auditory and somatosensory perturbations of speech
- Currently, FACTS does not include adaptive control to account for changes in behavior over time

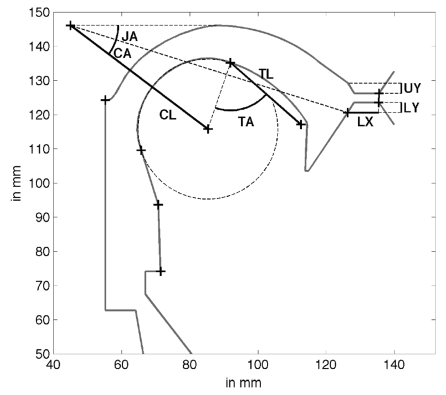
Modelling sensorimotor adaptation in a state feedback control model



A simplified state-feedback controller. The lower-level (articulatory) controller in FACTS has this structure.

- Adaptation is driven by sensory errors (as caused by, e.g., an external perturbation of vowel formants)
- Errors can update either the forward model or the control policy, or both
- If errors update the forward model, this model must be used in planning future movements.
- If errors update the forward model, do they update the state prediction model, the sensory prediction model, or both?

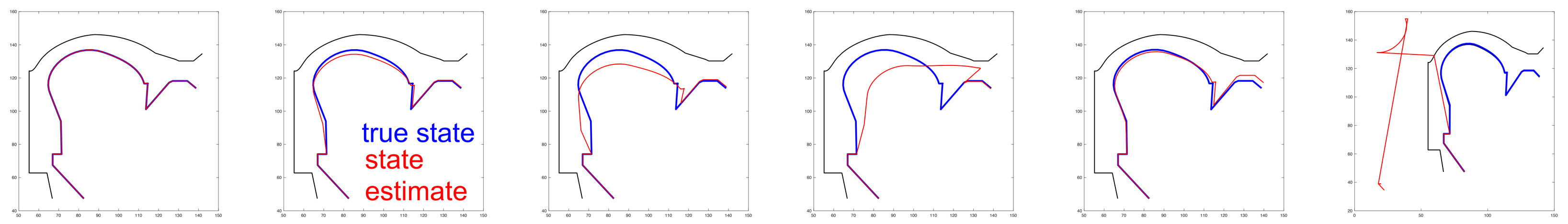
Learning the state and sensory prediction models



- Configurable Articulatory Synthesizer (CASY) used as the vocal tract model for FACTS simulations
- Auditory prediction requires both process and observation models.
  - **Process model**: predict the next articulatory state from the current state and current motor command (x[t], u[t] → x[t+1])
  - **Observation model**: predict the current sensory state from the current articulatory state (x[t+1] → y[t+1])
- Somatosensory prediction uses an identity function.
- *Training Data for learning models*: ~2900 sweeps of the CASY synthesizer covering different regions of the vocal tract

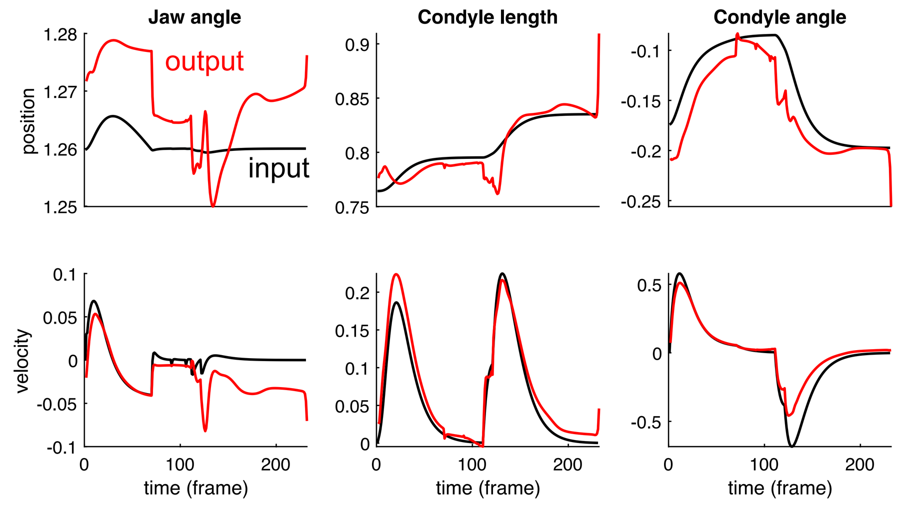
Locally Weighted Projection Regression

- Point-to point prediction
- Learns a local receptive field mapping for different regions of the input-output space
- Used for process and observation models
- More interpretable relative to DNN-based models
- As implemented, inaccurate for process model, which leads to model instability



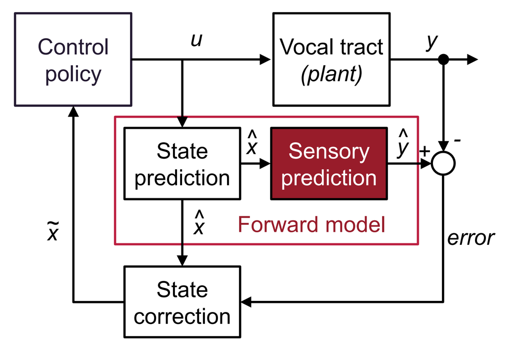
Recurrent Neural Networks (LSTMs)

- Sequence to sequence prediction
- Learns a nonlinear mapping of the input-output space
- Black box model. Interpretability not straightforward.
- Investigated for process model because of instability in LWPR models

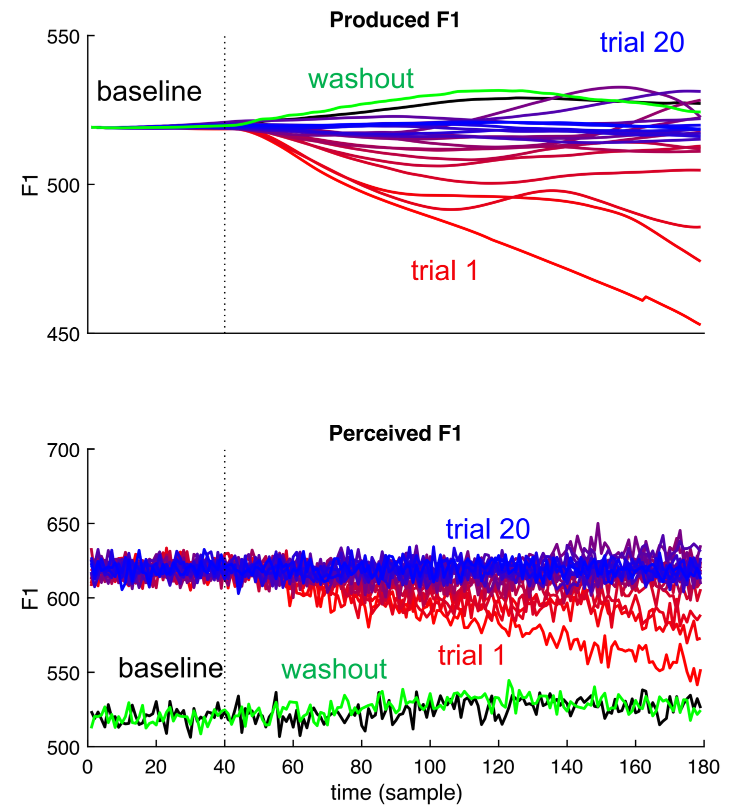


Modeling adaptation in FACTS

Sensorimotor adaptation as changes to the sensory prediction model

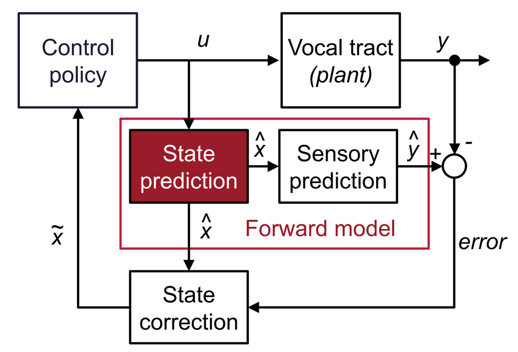


- Updates to LWPR sensory prediction model on a trial-by-trial basis
- After baseline trial (**black**), model exposed to 20 trials +100 Hz perturbation of F1(**red→blue**).
- A final washout trial (**green**) with no perturbation tests for adaptation.



- Updates to LWPR model do cause changes to behavior.
- Learning does not oppose perturbation
- Model learns to predict auditory perturbation, leading to loss of compensatory response (as seen on trial 1)
- Potential for adaptation only if model could be used to optimize motor command

Sensorimotor adaptation as changes to the state prediction model



Goal:

- Update LSTM state prediction model on a trial-by-trial basis
- Updating state prediction model may provide a way to model adaptation without needed to incorporate forward models into control search/optimization.

Current problems and potential solutions

- Sequence prediction
  - Model currently trained on whole-trial sequences.
  - Need to predict a single time point.
  - Lose desirable smoothing with single-point prediction.
- Model accuracy
  - How to assess accuracy
  - What is accurate enough?