Complexity patterns underlying speech production activity

Leonardo Lancia[1], Jinyu Li[1], Louis Goldstein[2]
[1]laboratoire de Phonétique et Phonologie (CNRS/Sorbonne-Nouvelle).
[2]Department of Linguistics, University of Southern California.

During speech production the sensorimotor system is subject to two complementary tendencies :

a tendency toward **Particulation** that, by favoring the emergence of distinct task-specific functional modules, permits developping complex behaviour;

and a tendency toward **Integration** that, by favoring the emergence of globally coherent behaviour, permits reducing motor control complexity.

Objective: **To study the interplay between these tendencies, we quantify the complexity of speech production patterns.**

Two different perspectives can be taken in the analysis of speech production :

At the symbolic level, we can describe an inventory of sounds via features. In other words, we are interested in the position of the speech production system in a space of symbolic, articulatory, acoustic features.

To characterize speech as a physical processes, we need to consider the evolution over time of the parameters of interests.

We define two measures :

Spatial complexity depends on the variability of the acoustic or articulatory events observed.

Temporal complexity depends on the variability of their durational features.

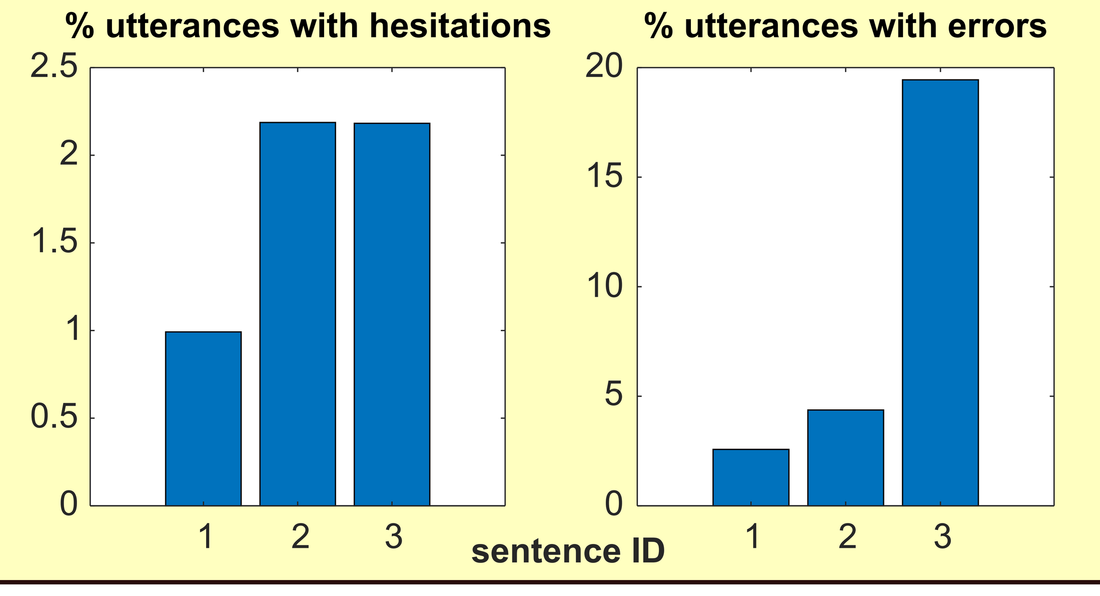
Experiment

sentence reading under Delayed Auditory Feedback (DAF). Speakers exposed to this perturbation increase the durations of their syllables to realign their motor commands to the delayed feedback.

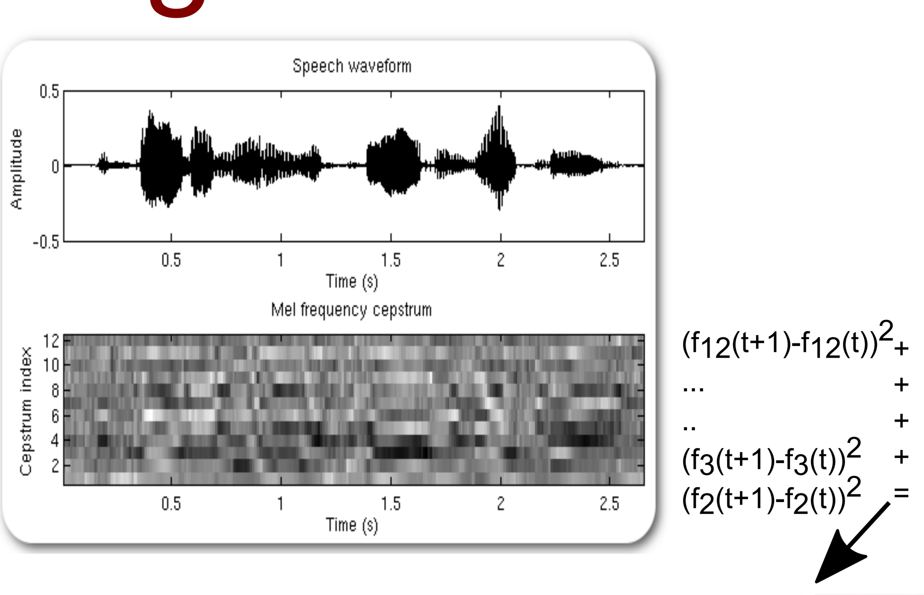
- 6 delays: 0, 0.06s, 0.09s, 0.12s, 0.15s, 0.18s.
- Three sentences with increasing probability to induce speech errors or hesitations:

1) /val'mõ vu'lɛ 'vwaʁ lə 'vɔl/
2) /lə nɔʁ'mɑ̃ ɔʁ nɔʁ'mə 'mɔʁ/
3) /ma'mɑ̃ e ma'mi ma'ni ma'mɑ̃/

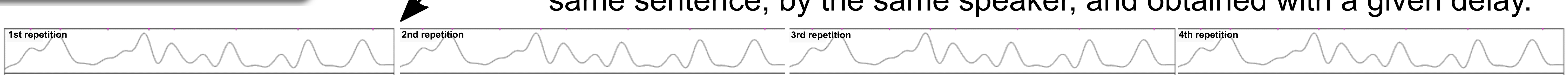
(Red typeface indicates priming and inverted sequences)



Signals



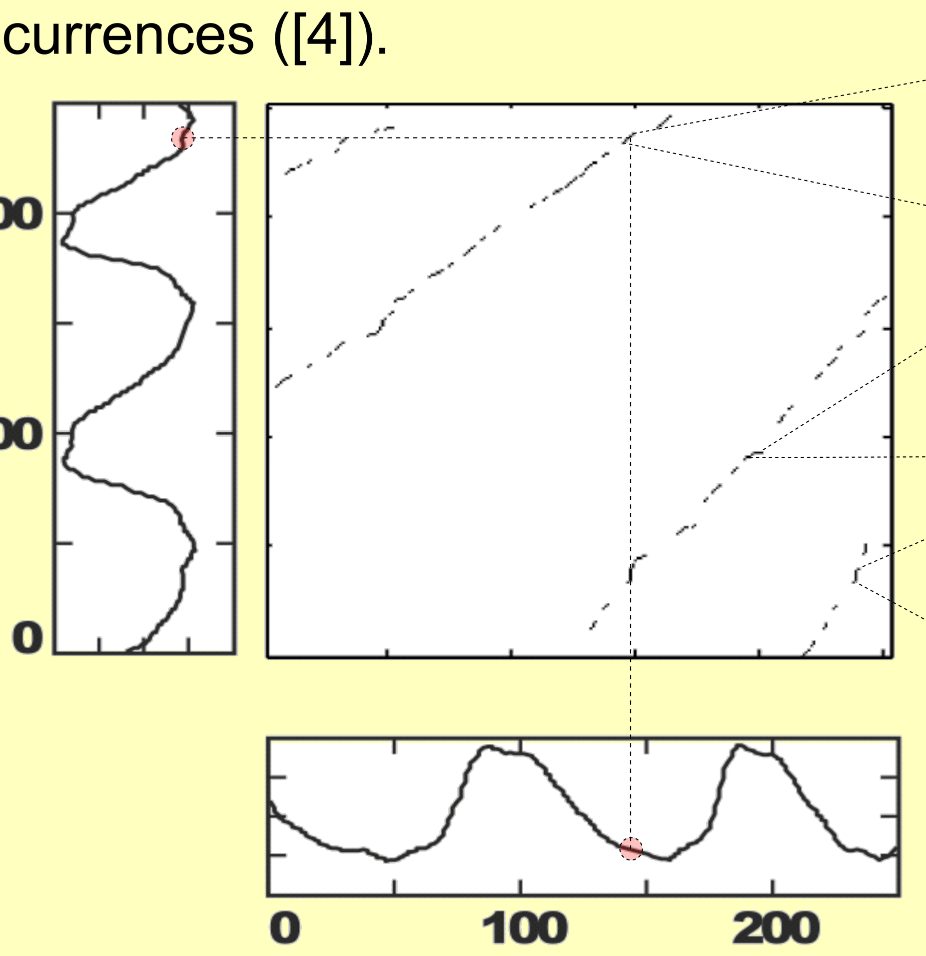
The total amount of frame by frame change of the first 13 MFCCs is strongly and systematically correlated with changes of vocal tract configurations (see [1]).
We took coeffs. 2-13 In order to focus on vocal tract changes.
We concatenated the MFCCs change trajectories obtained from the repetitions of the same sentence, by the same speaker, and obtained with a given delay.

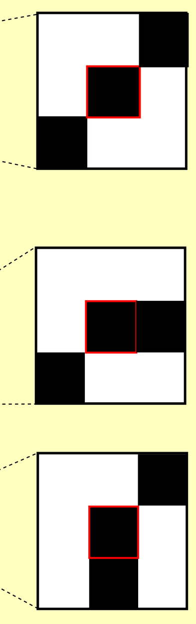


Analyses

From each time series we computed a Recurrence Plot (RP) in which a black dot at coordinates i,j indicates the dynamics observed at time i recur a time j (the distance between the time series states at the two time points is very small). To get meaningful RPs from goal-oriented behavior, we had to use non uniform embedding ([2]) and an RP cleaning algorithm [3].

Spatial complexity: the entropy of the distribution of the distances between pairs of time series states corresponding to recurrences ([4]).





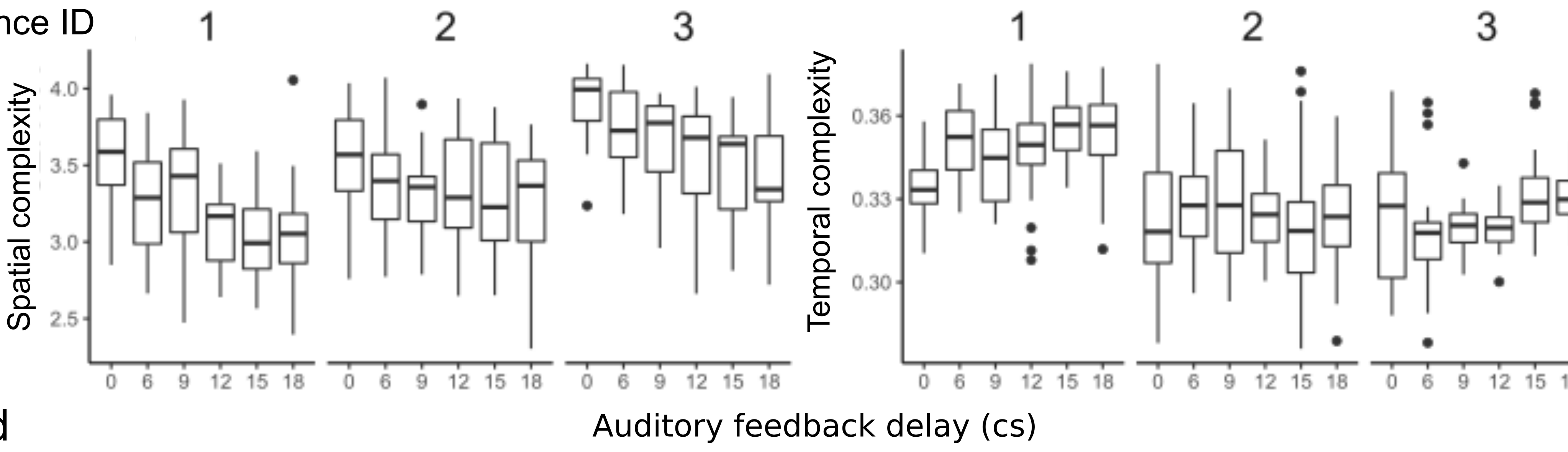
Diagonal: same rate of change

Slope < 0.5 : point on the x axis faster

Slope > 5 : point on the y axis faster

Temporal complexity: The locations of the dots in the 3x3 neighborhood of a recurrence at coords i,j depend on the differences between the two rates of change of the system at times i and j. We compute the entropy of the distribution of the probabilities of observing each of the 256 possible neighborhoods in the RP (see [5]).

Results



Results show the complementary nature of spatial and temporal complexity in speech motor control. Indeed the two measures respond in opposite (but predictable) directions to changes in the difficulty of the speech production task, and to changes in feedback delay.

References

Goldstein, L. (2019). The Role of Temporal Modulation in Sensorimotor Interaction. Frontiers in Psychology, 10, 2608. [2] Zhang, J. (2018). Low-dimensional approximation searching strategy for transfer entropy from non-uniform embedding. PloS one, 13(3), e0194382. [3] Lancia, L., Krasovitsky, G., &Stuntebeck, F. (2019). Coordinative patterns underlying cross-linguistic rhthmic differences. JPhon, 72, 66-80. [4] Eroglu, D., Peron, T. K. D., Marwan, N., Rodrigues, F. A., Costa, L. D. F., Sebek, M., ... & Kurths, J. (2014). Entropy of weighted recurrence plots. Phys. Rev. E, 90(4), 042919. [5] Corso, G., Prado, T. D. L., Lima, G. Z. D. S., Kurths, J., & Lopes, S. R. (2018). Quantifying entropy using recurrence matrix microstates. Chaos, 28(8), 083108.