The Traces of Inner Life

Lecture 06a (Analysis III)

Alessandro Vinciarelli

Outline

- Social Signals
- Speech Articulation and Tract Variables
- Articulation as a Dynamic Process
- Conclusions

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Social Signals

"[…] acts or structures that influence the behavior or internal state of other individuals."

Mehu and Scherer, "A psycho-ethological approach to Social Signal Processing"
Cognitive processing, 13(2), pp.397-414, 2012.

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Social Signals

"actions whose function is to bring about some reaction or to engage in some process."

Brunet and Cowie, "Towards a conceptual framework of research on Social Signal Processing", Journal on Multimodal User Interfaces, 6(3), pp.101-115, 2012.

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Social Signals

"[...] communicative or informative signals which [...] provide information about social facts."

Poggi and D'Errico, "Social signals: a framework in terms of goals and beliefs", Cognitive Processing, 13(2), pp.427-445, 2012.

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Social Signals as Physical Traces

- Social signals are the physical, machine detectable traces of social and psychological phenomena;
- If this was not the case, it would not be possible for them to influence others or attract reactions;
- Similarly, it would not be possible to provide information about social facts;
- In some cases, their identification is simple (e.g., a smile), in others it is more challenging (e.g., the “speaking style” of depression patients).

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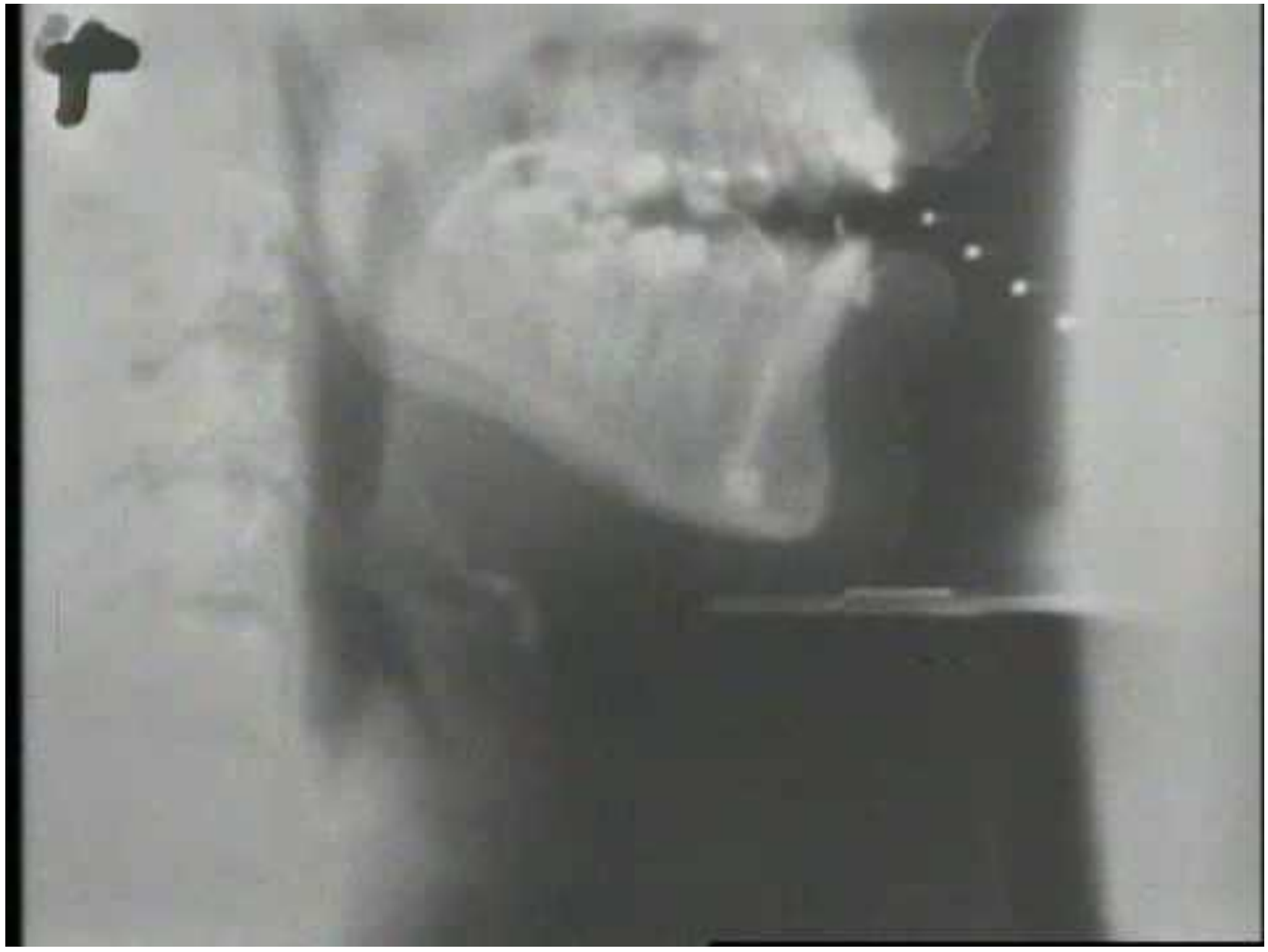
Articulation



Articulation

XRMB Dataset

Speakers	Number	Median Age	Q1 Age	Q2 Age
Female	25	21.3	20.2	24.7
Male	21	20.8	20.0	22.4
Total	46	21.1	20.1	23.9

- The data were collected in the early nineties, before experiments of this type with X-Rays were considered too dangerous;
- The position of the pellets is sampled at 145 Hz, the speech signal is samples at 22.05 kHz.

Westbury, Turner and Dembowski, “X-Ray microbeam speech production database user’s handbook”, University of Wisconsin Technical Report, 1994

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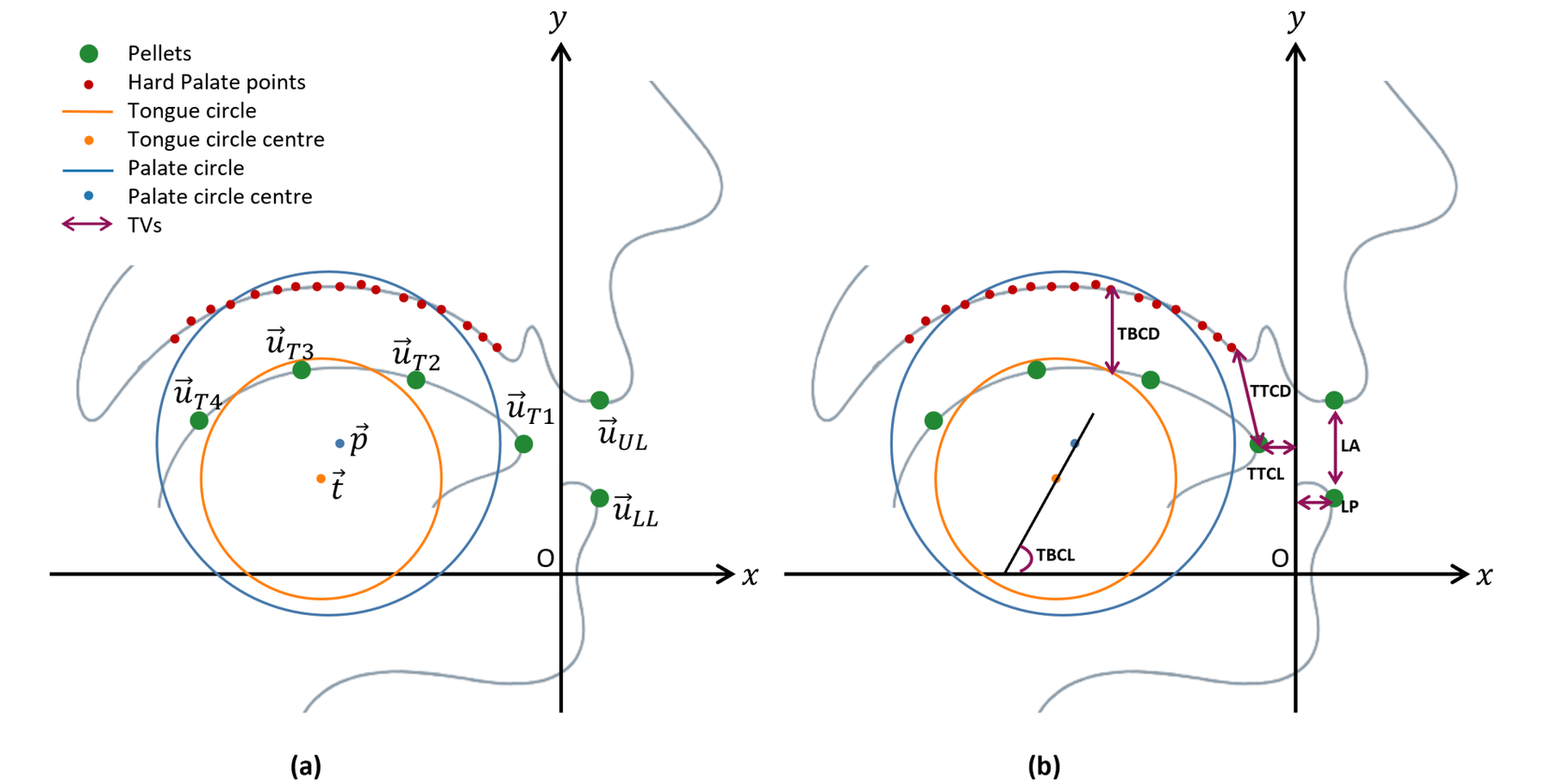
Lip Aperture



(a) (b)

- The Euclidean distance between upper and lower lip: $||\vec{u}_{LL} - \vec{u}_{UL}||_2$.

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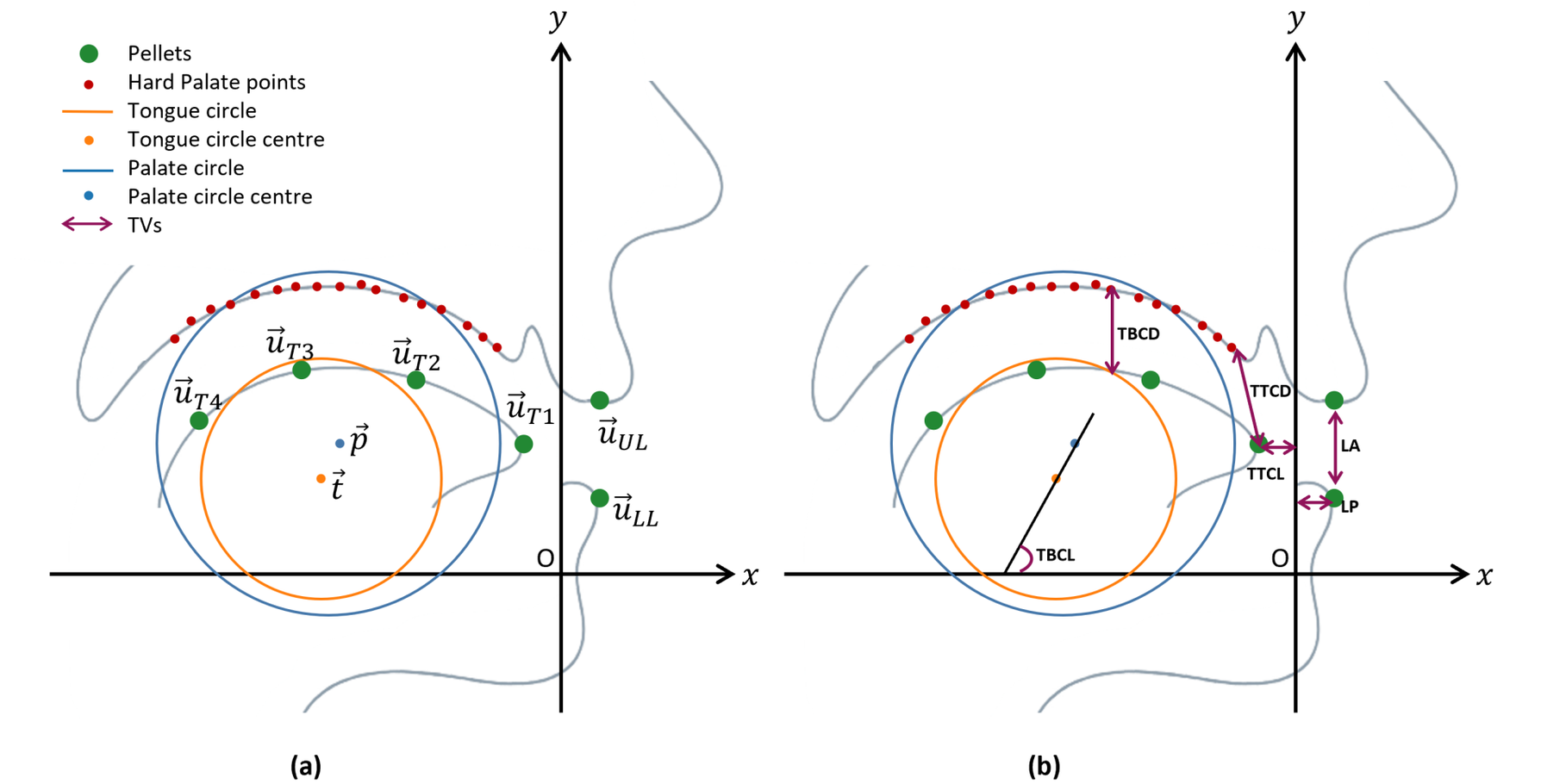
Lip Protrusion



(a) (b)

- The horizontal distance of the LL pellet from the origin along the x axis: x_{LL}.

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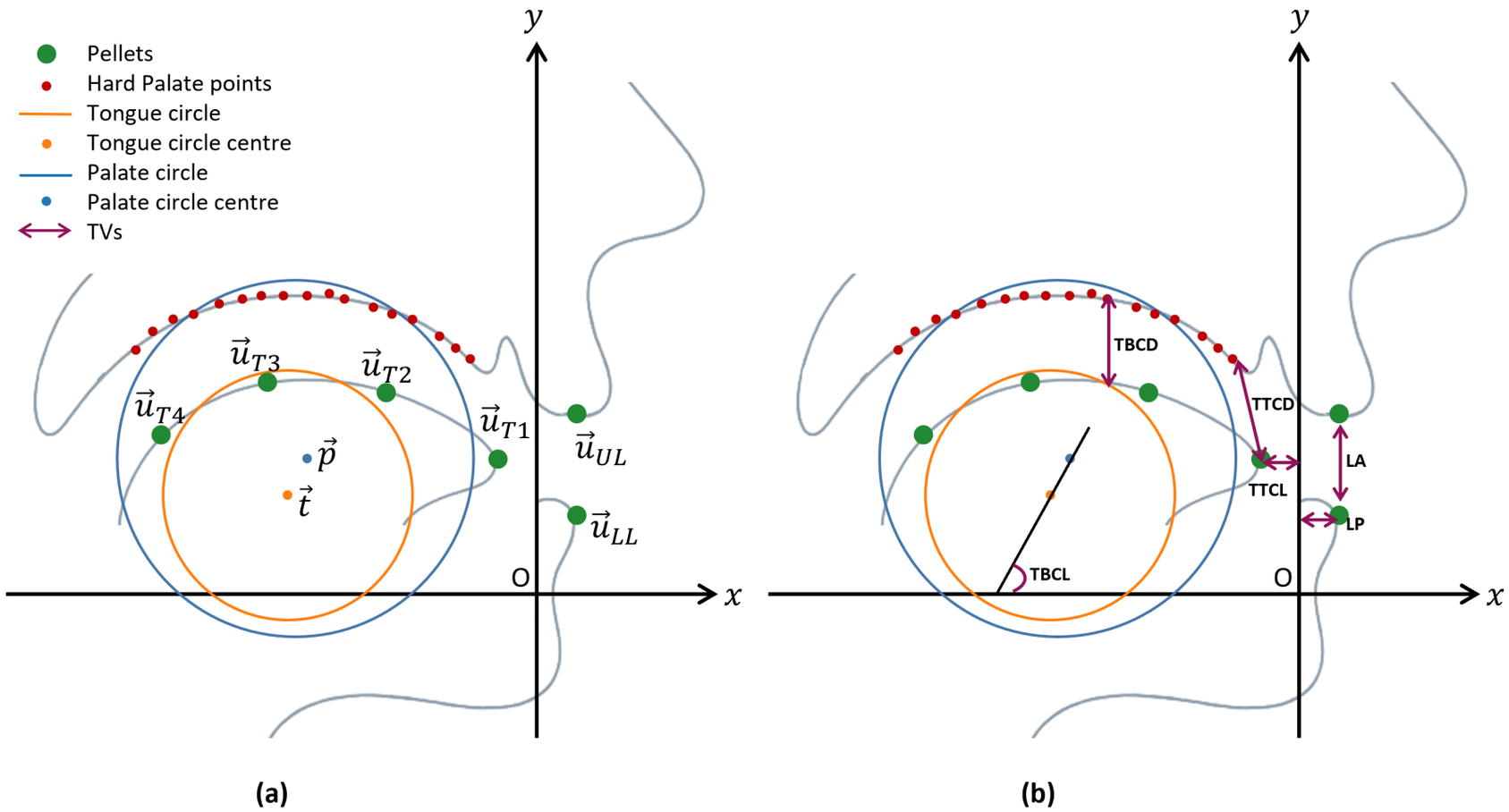
Tongue Body Constriction Location



(a) (b)

- The angle between the x axis and the line passing through the centres of tongue and palate: $\arctan\left[(y_T - y_P)/(x_T - x_P)\right]$.

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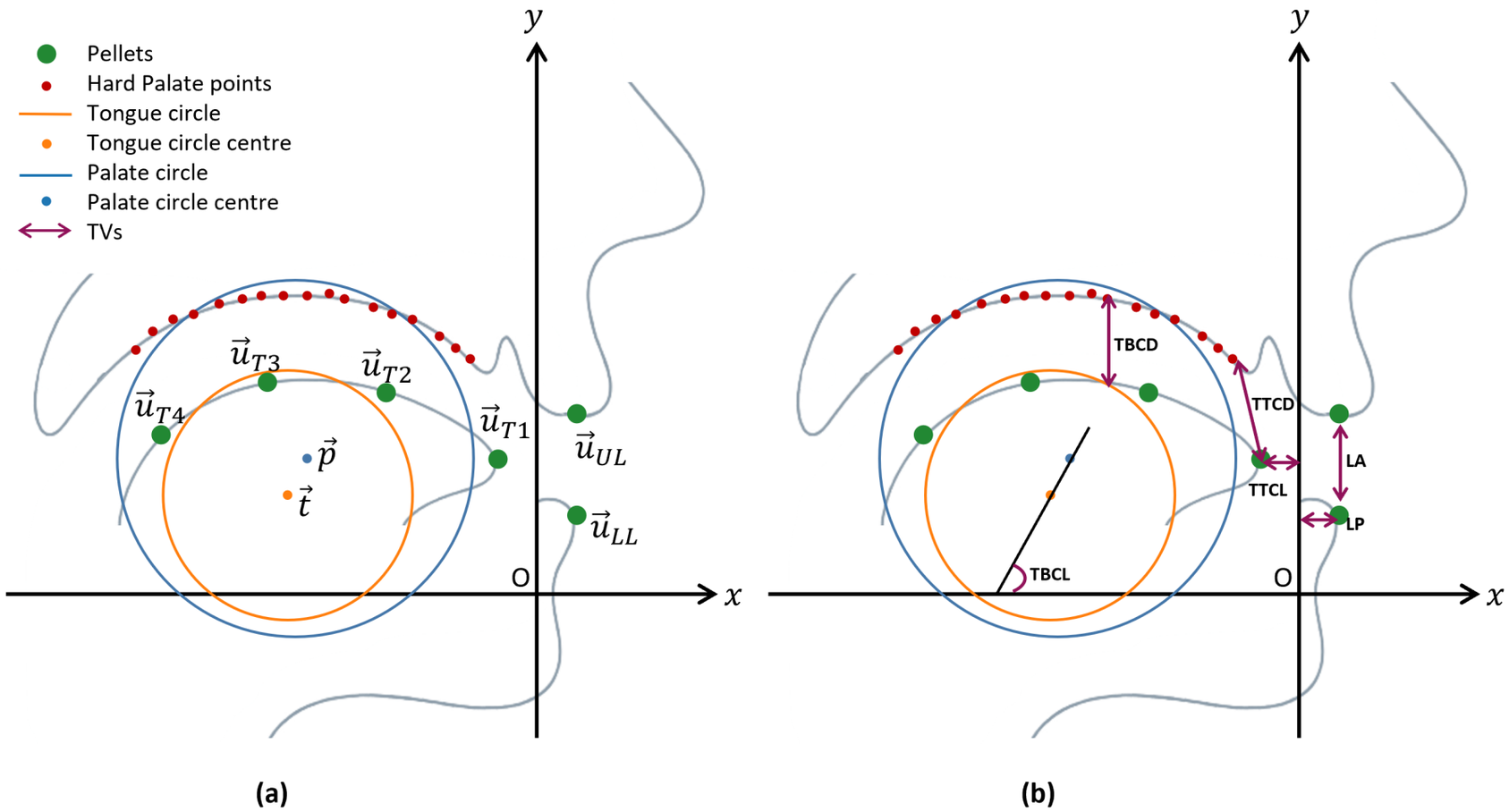
Tongue Body Constriction Degree



(a) (b)

- Shortest distance between any point $\vec{u}_T$ on Tongue Circle (between $\vec{u}_{T2}$ and $\vec{u}_{T4}$) and any point on Palate Circle: $\min_{\vec{u}_P, \vec{u}_T} ||\vec{u}_P - \vec{u}_T||_2$.

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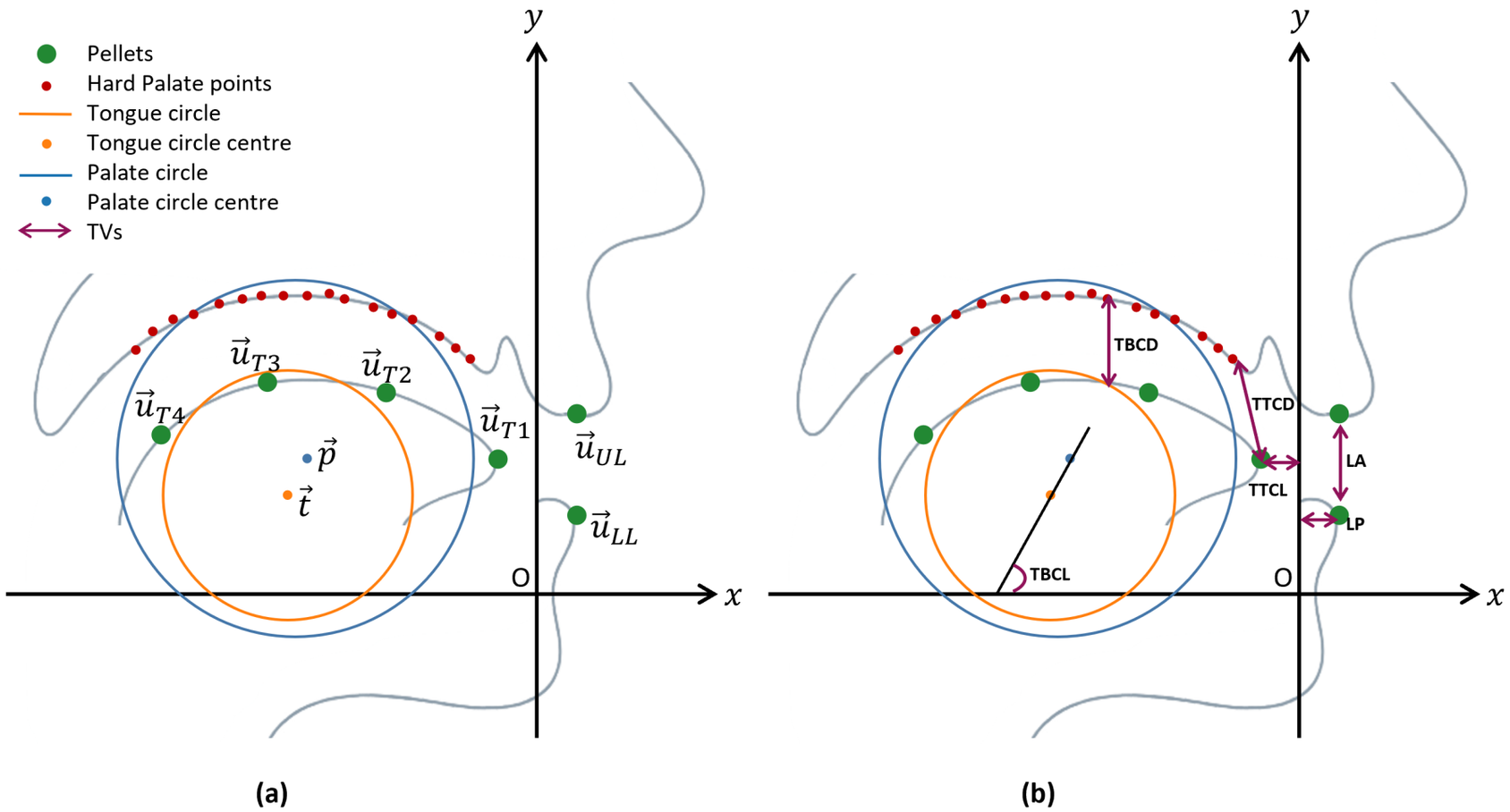
Tongue Tip Constriction Location



(a) (b)

- Horizontal distance between $\vec{u}_{T1}$ and y axis: x_{T1}.

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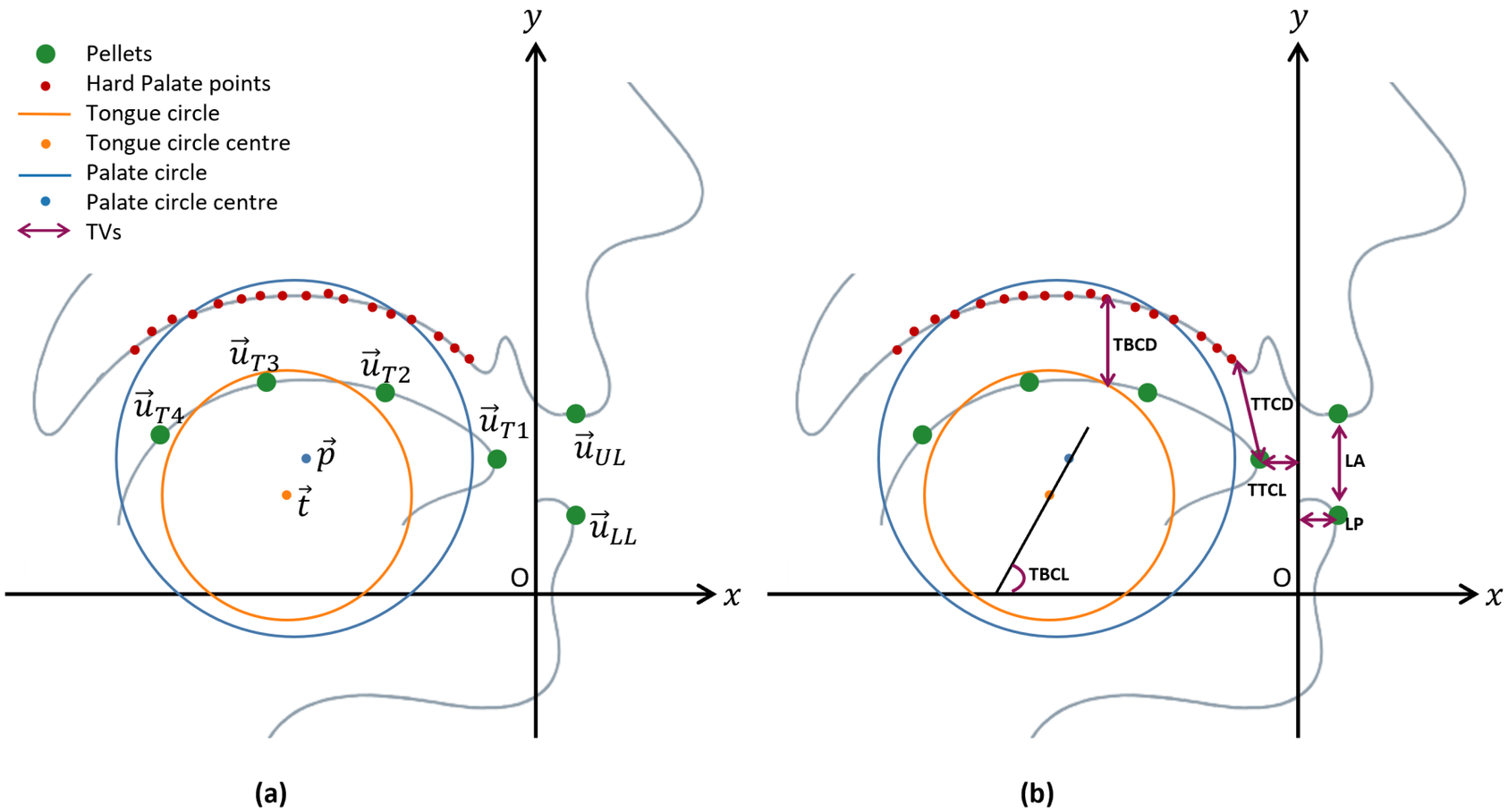
Tongue Tip Constriction Degree



(a) (b)

- Shortest distance between $\vec{u}_{T1}$ and any point on Palate Circle: $\min_{\vec{u}_P} ||\vec{u}_P - \vec{u}_{T1}||_2$.

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Tract Variables

- The six measurements of the previous slides are referred to as Tract Variables;
- They account for the configuration of the articulators during the speech production process;
- The articulators are the organs that shape the sounds produced during speech emission;
- The speech production process is the most complex motor process performed by the human body;
- Psychomotor retardation is likely to impact negatively the speech production process.

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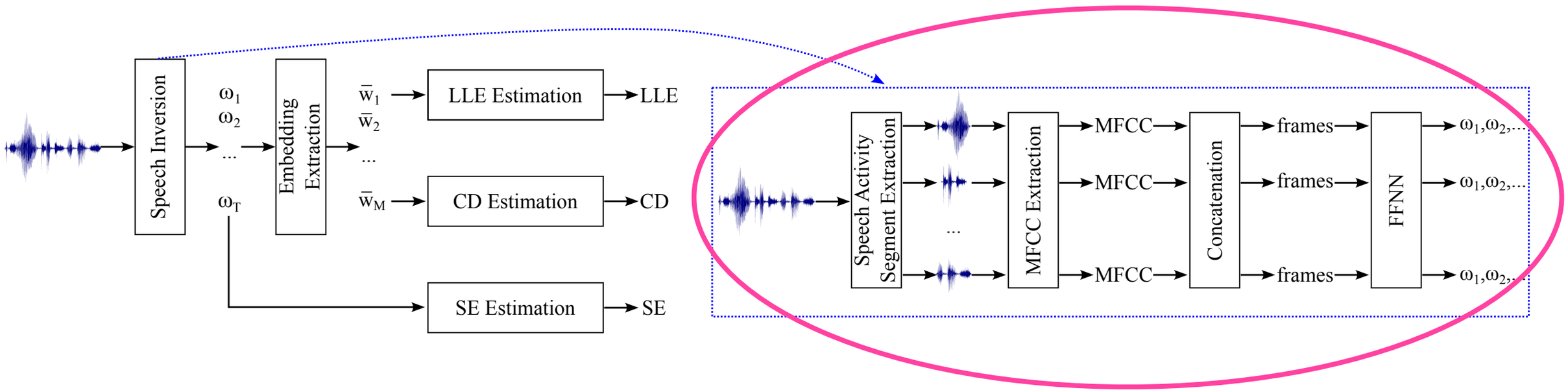
Speech Inversion



- Speech Inversion is the process aimed at automatically mapping speech signals into sequences of Tract Variables;
- The Tract Variables are extracted at regular time-steps of 10 ms from 30 ms long windows (sampling frequency of 100 Hz).

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Inversion Performance

	LA	LP	TBCL	TBCD	TTCL	TTCD	Avg.
Sivaraman 2019	0.856	0.613	**0.866**	0.745	0.707	0.907	0.782
Attia et al. 2023	0.868	0.590	0.742	0.780	0.597	0.893	0.745
Attia et al. 2024a	0.860	0.710	0.742	0.775	0.742	0.898	0.788
Attia et al. 2024b	**0.878**	**0.724**	0.743	0.809	**0.787**	**0.925**	0.810
This Work	0.855	0.714	0.816	**0.841**	0.773	0.897	**0.816**

- The speech inversion process performs at the level of the state of the art.

Altalhi, Guha and Vinciarelli, “Depression Markers in Speech: An Approach Based on Tract Variables Dynamics”, under review, 2026

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Articulation as a Dynamic System

- The speech production apparatus can be thought of as a dynamical system, that is, a physical system that changes state over time;
- The articulators and, correspondingly, the Tract Variables can be considered as the observables of the dynamical system;
- The Theory of Dynamical Systems can be used as a means to model the speech production process and, possibly, to identify differences between depressed and non-depressed speakers.

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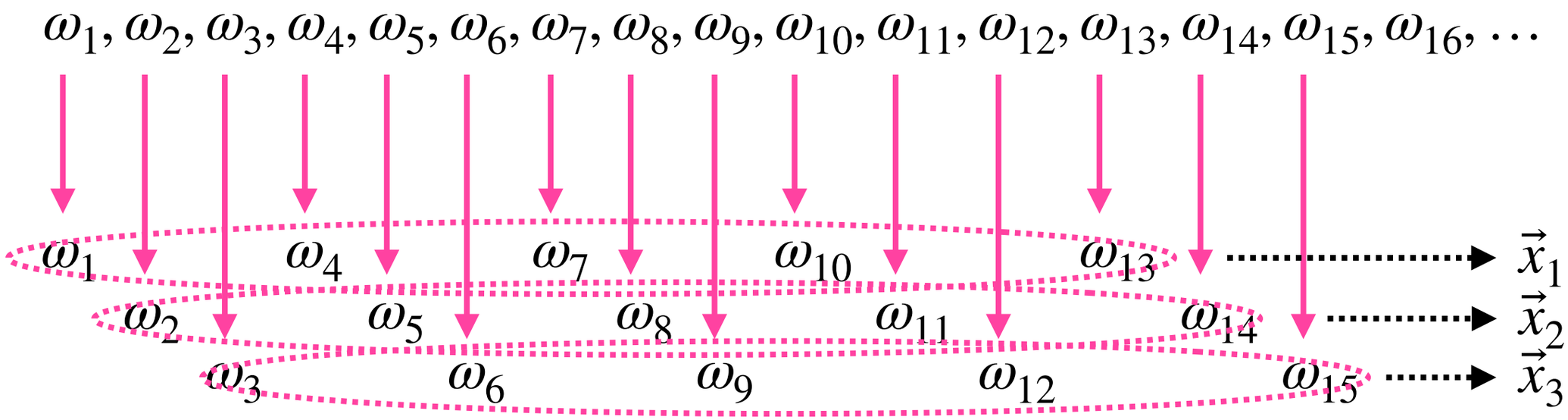
Embedding Extraction



- The “distance” between consecutive components in the embeddings is called the delay τ;
- According to the Taken’s Theorem, the embeddings $\vec{x}_i$ are representations of the dynamic system’s state.

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Embedding Space

- The space of the embeddings corresponds to all possible states a dynamical system can take;
- A trajectory in the embedding space corresponds to the evolution of the system over time;
- The properties of the embeddings' space and of the embeddings' trajectories provide information about the properties of the system;
- The reason for expecting differences between depressed and non-depressed speakers is that the pathology interferes with language processing in the brain.

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The Data

Condition	Age	Female	Male	Low Education	High Education
Control	47.6 ± 12.6	42	12	19	33
Depressed	47.6 ± 12.0	37	18	23	31
Total	47.6 ± 12.2	79	30	42	64

- No differences between Control and Depressed (diagnosed by professional psychiatrists) in Gender, Age and Education;
- Publicly available at https://github.com/androidscorpus/data.

Irons, “Depression”, Palgrave, 2014

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#1

#2

- All 109 participants were asked to read the same text (“The North Wind and the Sun” by Aesop);
- The goal is to eliminate variance resulting from differences in spoken content;
- The depression patient is record #2.

Tao, Esposito and Vinciarelli, “The Androids Corpus: A New Publicly Available Benchmark for Speech Based Depression Detection”, Proceedings of Interspeech, 2023

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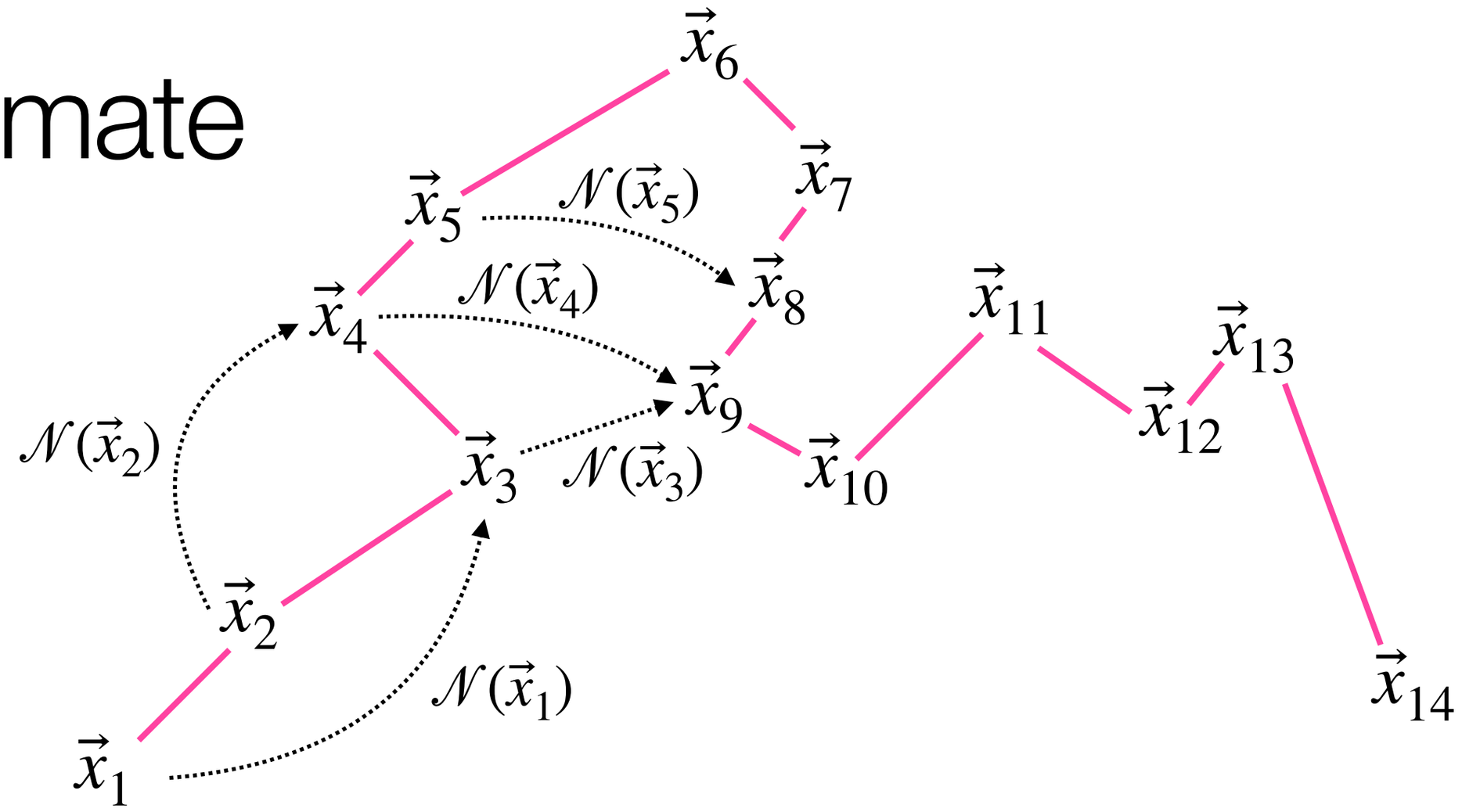
LLE Estimate



- $\mathcal{N}(\vec{x}_j)$ is the nearest embedding;
- $d_j(0) = ||\vec{x}_j - \mathcal{N}(\vec{x}_j)||_2$ is the distance between embedding $\vec{x}_j$ and its nearest neighbour (with $\Delta t > 1/F$, where F is the sampling frequency).

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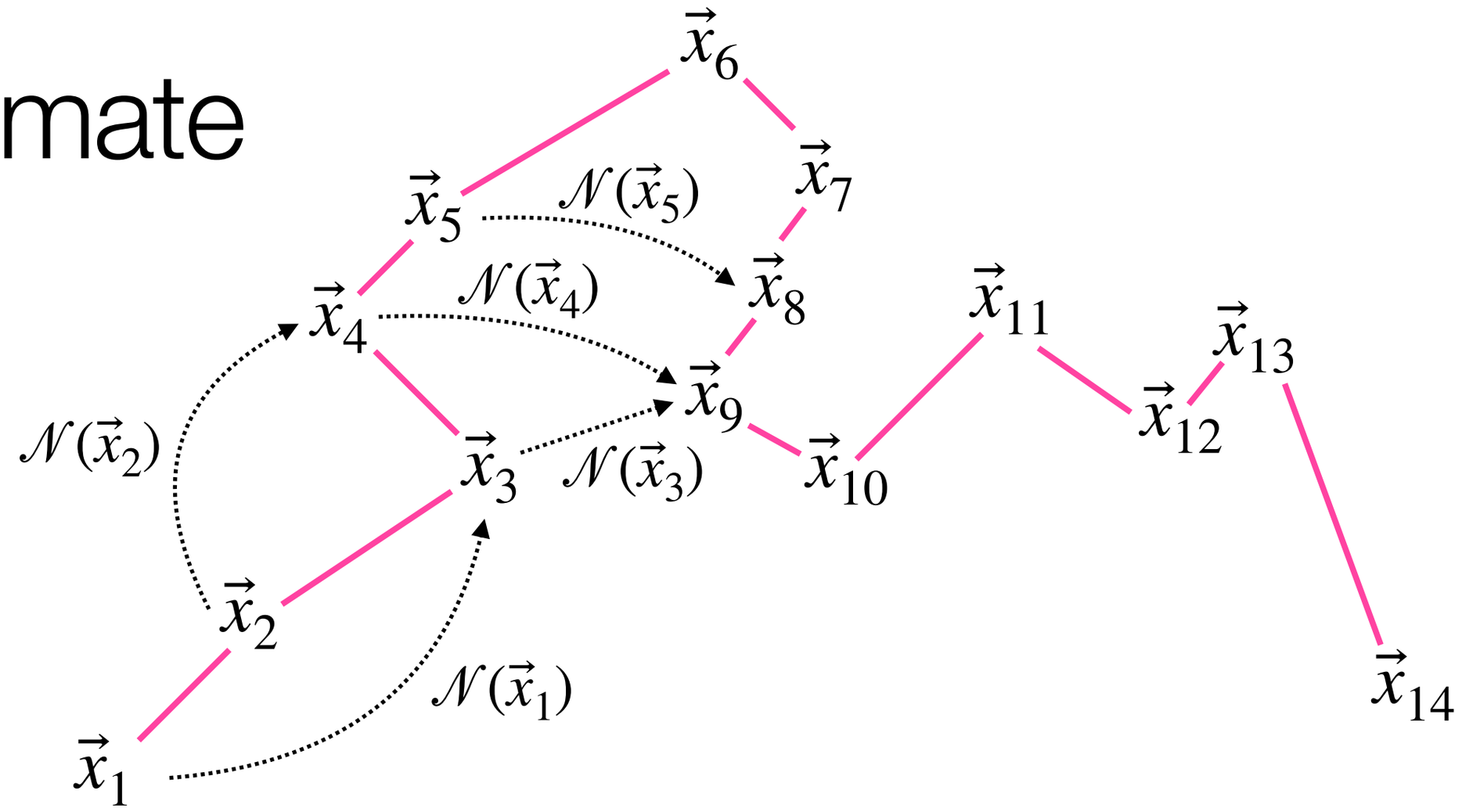
LLE Estimate



- $d_j(i) = ||\vec{x}_{j+i} - \mathcal{N}(\vec{x}_{j+i})||_2$ accounts for how the distance $d_j(0)$ evolves after i steps.
- Under the exponential divergence assumption, $d_j(i) \simeq d_j(0)e^{\lambda_1 i\Delta t}$, where $\Delta t = 1/F$.

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LLE Estimate

$$\log d_j(i) = \log d_j(0) + \lambda_1 i \Delta t$$

- The expression suggests that $\log d_j(i)$ grows linearly with the time;
- The best fit of the points $d_j(0), d_j(1), \ldots, d_j(M - j)$ has the Largest Lyapounov Exponent as slope.

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LLE (Read Speech)

TV	Control	Depressed	P-value	Cliff's Delta
LA	0.021±0.005	0.023±0.006	0.104	0.18
LP	0.020±0.005	0.025±0.007	**<0.001**	0.38
TTCL	0022±0.006	0.026±0.007	**0.001**	0.34
TTCD	0.020±0.004	0.024±0.006	**0.002**	0.28
TBCL	0.022±0.006	0.029±0.008	**<0.001**	0.41
TBCD	0.025±0.008	0.030±0.009	**<0.001**	0.37
Lips	0.021±0.004	0.024±0.005	**0.003**	0.31
Tongue	0.022±0.004	0.027±0.006	**<0.001**	0.51
All	0.022±0.003	0.026±0.005	**<0.001**	0.50

- Statistically significant differences for most TVs and TV groups.

Altalhi, Guha and Vinciarelli, "Depression Markers in Speech: An Approach Based on Tract Variables Dynamics", under review, 2026

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LLE (Spontaneous Task)

TV	Control	Depressed	P-value	Cliff's Delta
LA	0.029±0.005	0.032±0.007	0.023	0.23
LP	0.032±0.006	0.033±0.006	0.234	0.09
TTCL	0028±0.005	0.030±0.006	0.035	0.22
TTCD	0.028±0.005	0.032±0.008	0.013	0.26
TBCL	0.033±0.007	0.035±0.008	0.118	0.15
TBCD	0.034±0.005	0.036±0.007	0.045	0.19
Lips	0.021±0.004	0.024±0.005	**0.049**	0.19
Tongue	0.022±0.004	0.027±0.006	**0.030**	0.23
All	0.022±0.003	0.026±0.005	**0.024**	0.23

- Statistically significant differences only for TV groups, none for individual TVs.

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LLE Differences

- The LLE difference is statistically significant for all Tract Variables except LA and for all groups of Tract Variables for read speech;
- For spontaneous speech, only groups of Tract Variables show statistically significant differences;
- It appears to be a good biomarker for read speech;
- The LLE accounts for the predictability and it appears to be higher for depressed speakers (lower predictability) in read speech;
- The literature confirms and shows that the feature correlation tends to be lower.

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Correlation Dimension

$$C(\rho) = \frac{2}{M(M-1)} \sum_{i=1}^{M} \sum_{j=i+1}^{M} \Theta\left(\rho - \|\vec{w}_i - \vec{w}_j\|_2\right)$$

- The intrinsic dimensionality D of the embedding space is estimated through the fraction of pairs that lie within distance ρ from each other;
- The relationship $\ln C(\rho) \propto D \ln \rho$ allows one to estimate the value of D;
- Higher dimensionality, means that the dynamical system has more degrees of freedom.

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CD (Read Speech)

TV	Control	Depressed	P-value	Cliff's Delta
LA	3.66±0.32	3.47±0.31	**0.001**	0.33
LP	3.62±0.29	3.47±0.27	**0.008**	0.26
TTCL	3.42±0.33	3.34±0.37	**0.022**	0.22
TTCD	3.35±0.36	3.16±0.36	**0.004**	0.29
TBCL	3.16±0.33	2.94±0.31	**<0.001**	0.37
TBCD	3.45±0.36	3.24±0.38	**0.001**	0.34
Lips	3.64±0.22	3.47±0.23	**<0.001**	0.40
Tongue	3.35±0.23	3.17±0.25	**<0.001**	0.40
All	3.46±0.17	3.28±0.21	**<0.001**	0.49

- Statistically significant differences for all TVs and TV groups.

Altalhi, Guha and Vinciarelli, "Depression Markers in Speech: An Approach Based on Tract Variables Dynamics", under review, 2026

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CD (Spontaneous Speech)

TV	Control	Depressed	P-value	Cliff's Delta
LA	3.19±0.23	3.10±0.28	**0.006**	0.27
LP	3.30±0.21	3.21±0.31	**0.020**	0.22
TTCL	3.20±0.24	3.06±0.36	**0.013**	0.24
TTCD	2.90±0.21	2.73±0.30	**<0.001**	0.36
TBCL	2.63±0.18	2.50±0.28	**0.002**	0.32
TBCD	2.89±0.21	2.74±0.27	**0.001**	0.33
Lips	3.64±0.22	3.14±0.25	**0.007**	0.27
Tongue	3.35±0.23	2.77±0.25	**<0.001**	0.36
All	3.46±0.17	2.91±0.21	**0.001**	0.35

- Statistically significant differences for all TVs and TV groups.

Altalhi, Guha and Vinciarelli, "Depression Markers in Speech: An Approach Based on Tract Variables Dynamics", under review, 2026

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CD Differences

- The CD difference is statistically significant for all Tract Variables and for all groups of Tract Variables;
- It appears to be a good biomarker for both read and spontaneous speech;
- The CD accounts for the degrees of freedom of the speech production process, it is the dimensionality of the attractor, the set of all possible states;
- The CD tends to be higher for the control speakers, suggesting higher complexity;
- This is confirmed by the literature (depressed speakers tend to show lower variability).

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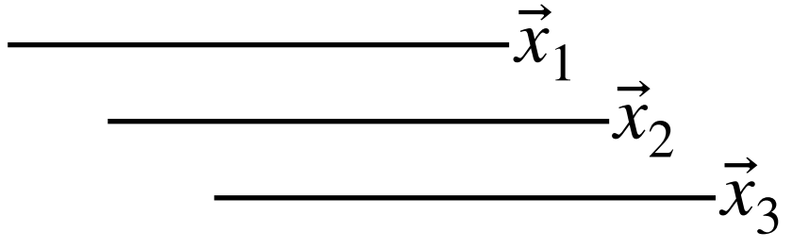
Sample Entropy

$\omega_1, \omega_2, \omega_3, \omega_4, \omega_5, \omega_6, \omega_7, \omega_8, \omega_9, \omega_{10}, \omega_{11}, \omega_{12}, \omega_{13}, \omega_{14}, \omega_{15}, \omega_{16}, \ldots$



- It is possible to count the number B of pairs $(\vec{x}_i, \vec{x}_j)$ such that $dist(\vec{x}_i, \vec{x}_j) < r$, where $dist(\,.\,)$ is a distance function;
- In this work, $dist(\vec{x}_i, \vec{x}_j) = \max_{k=[1,D]} |x_{ik} - x_{jk}|$, where D is the dimensionality of the $\vec{x}_i$.

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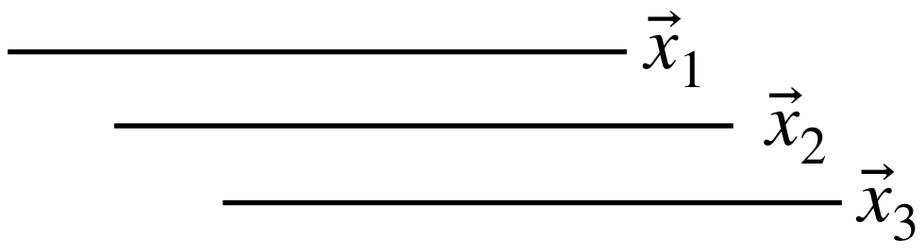
Sample Entropy

$\omega_1, \omega_2, \omega_3, \omega_4, \omega_5, \omega_6, \omega_7, \omega_8, \omega_9, \omega_{10}, \omega_{11}, \omega_{12}, \omega_{13}, \omega_{14}, \omega_{15}, \omega_{16}, \ldots$



- It is possible to count the number B of pairs $(\vec{x}_i, \vec{x}_j)$ such that $dist(\vec{x}_i, \vec{x}_j) < r$, where $dist(\,.\,)$ is a distance function;
- The dimensionality of the vectors has been increased from D to $D + 1$.

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Sample Entropy

$$SE(D, r, K) = -\ln\left(\frac{A}{B}\right)$$

- The parameter K is the total number of Tract Variables extracted from a recording;
- The SE does not measure the properties of the dynamical system or, at best, it does it only when $\tau = 1$.

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SE (Read Speech)

TV	Control	Depressed	P-value	Cliff's Delta
LA	0.26±0.06	0.23±0.06	**0.001**	0.33
LP	0.22±0.04	0.19±0.04	**<0.001**	0.39
TTCL	0.24±0.06	0.23±0.05	0.202	0.09
TTCD	0.26±0.05	0.25±0.06	0.119	0.13
TBCL	0.18±0.04	0.18±0.05	0.487	0.00
TBCD	0.16±0.04	0.14±0.04	**<0.001**	0.30
Lips	0.24±0.04	0.21±0.05	**0.002**	0.42
Tongue	0.21±0.03	0.20±0.03	**0.024**	0.22
All	0.22±0.03	0.21±0.03	**<0.001**	0.37

- Statistically significant differences for all TV groups, but only some of the individual TVs.

Altalhi, Guha and Vinciarelli, "Depression Markers in Speech: An Approach Based on Tract Variables Dynamics", under review, 2026

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SE (Spontaneous Speech)

TV	Control	Depressed	P-value	Cliff's Delta
LA	0.22±0.03	0.20±0.03	**0.001**	0.33
LP	0.19±0.03	0.17±0.03	**0.002**	0.32
TTCL	0.24±0.03	0.23±0.04	**0.024**	0.21
TTCD	0.24±0.03	0.23±0.04	0.213	0.09
TBCL	0.13±0.02	0.12±0.04	0.087	0.15
TBCD	0.13±0.02	0.11±0.02	**0.001**	0.33
Lips	0.20±0.03	0.18±0.03	**<0.001**	0.38
Tongue	0.20±0.02	0.19±0.03	**0.022**	0.22
All	0.20±0.02	0.21±0.02	**0.001**	0.33

- Statistically significant differences for all TV groups and most individual TVs.

Altalhi, Guha and Vinciarelli, "Depression Markers in Speech: An Approach Based on Tract Variables Dynamics", under review, 2026

SE Differences

- There are SE differences statistically significant for several Tract Variables and for all groups of Tract Variables;
- It appears to be a good biomarker for both read and spontaneous speech;
- The SE accounts for the repetitiveness of the speech production process, it measures how many new patterns appear;
- The SE tends to be lower for the depressed speakers, suggesting higher repetitiveness.

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Conclusions

- LLE, CD and SE can be used as depression biomarkers, that is, they can be used to discriminate between depressed and non-depressed speakers;
- Depressed speech appears to be less predictable (greater LLE), more constrained (lower CD) and more repetitive (lower SE);
- These effects explain a large number of observations presented in the literature;
- The biomarkers help clinicians to check the consistency between their judgment and measurable aspects of patients' behaviour.

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Thank You!

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