

# Analysing Articulatory Data with Vector Norms and Related Methods

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# Outline

- ▶ I will then talk about what we can and cannot do with these methods in time domain analysis of articulatory data these days. I will take short side trips to look at similar methods applied to other articulatory data. We have looked at tongue splines and lip videos and I will discuss what kind of challenges and understanding has resulted from those attempts. Finally, analysing 3D/4D ultrasound has been a recent major focus, but unfortunately frame rate issues are not so easy to solve.
- ▶ I will finish the talk by discussing why MRI would be very interesting to analyse with these methods – or adapted versions of them – and which definite and possible challenges one might come across.

# Introduction: The why

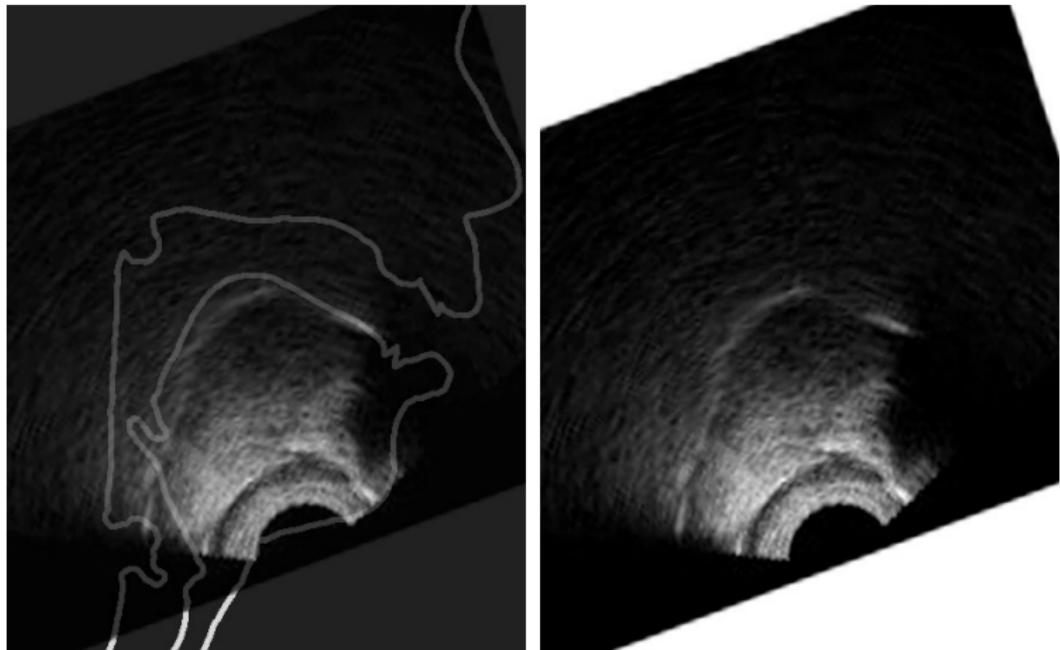
- ▶ Pre-speech articulation is interesting from several points of view, but analysing ultrasound videos manually is not great.
- ▶ In my thesis I concentrated on timing of utterance onset in both acoustics and articulation (Palo 2019).
- ▶ The data was high-speed tongue ultrasound from a delayed naming experiment – specifically one using the Rastle instructions (Rastle et al. 2005).
- ▶ 2D ultrasound has good time resolution: 80-120 fps in today's examples.

Classical	Stimulus (word) perception	Lexical etc processing	Movement initiation	Movement	Acoustic speech
Delayed	Lexical etc processing	Stimulus (beep) perception	Movement initiation	Movement	Acoustic speech

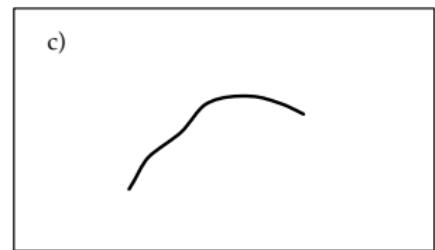
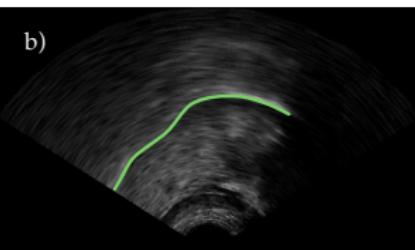
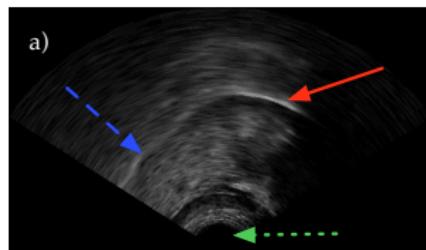
## Introduction: The why

- ▶ When trying to identify movement onset in greyscale videos with a lot of speckle 'noise', it doesn't take long to grow a desire for an easier way.
- ▶ The speckle 'noise' maybe caused by a number of factors including bubbles in the acoustic gel between the chin and the probe, and more interestingly changes in internal structures of tissues – such as muscle fibres tensing and relaxing.

What is being imaged by tongue ultrasound?



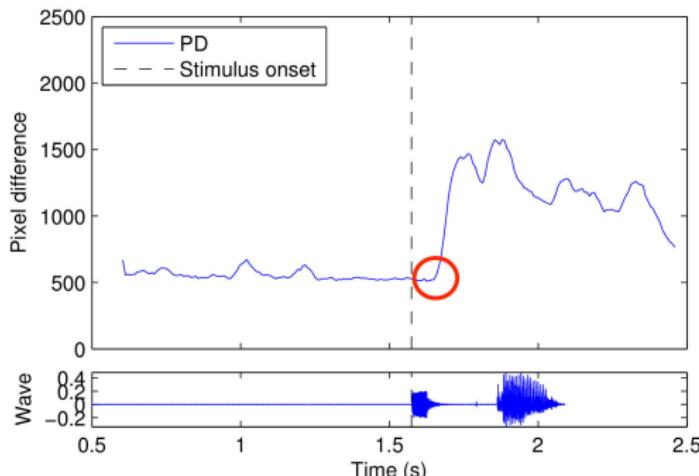
# Where is the tongue?



# Pixel Difference (PD)

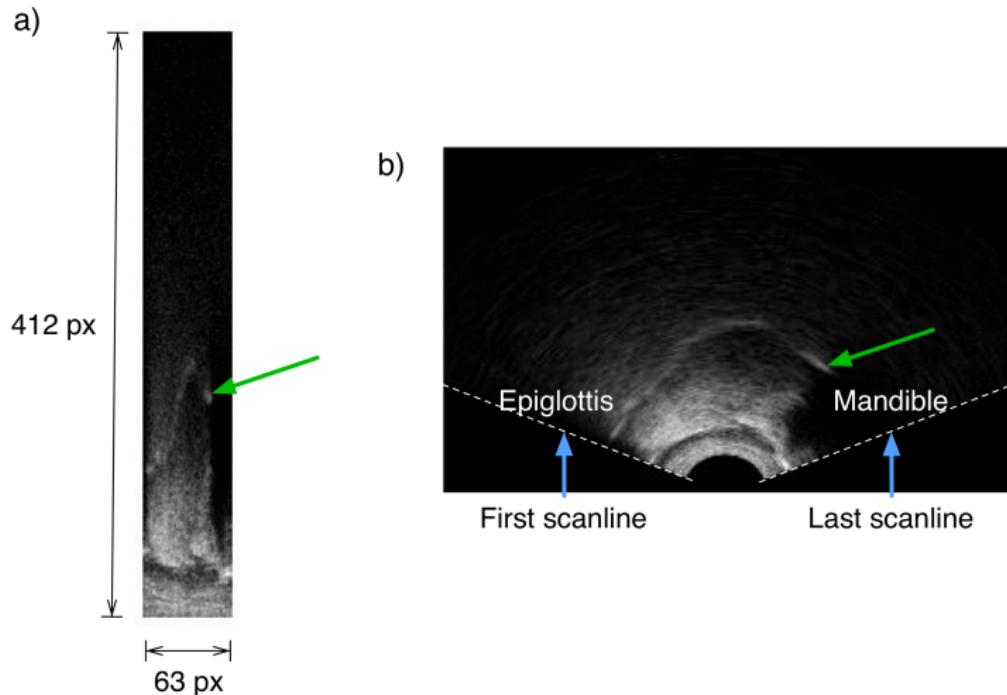
- The first tool out of the box happened to work adequately – and so for my thesis I used Euclidean distance or  $l_2$ -norm to identify articulatory onsets:

$$l_2(t + 0.5) = \sqrt{\sum_{i,j} (x(i, j, t + 1) - x(i, j, t))^2}$$

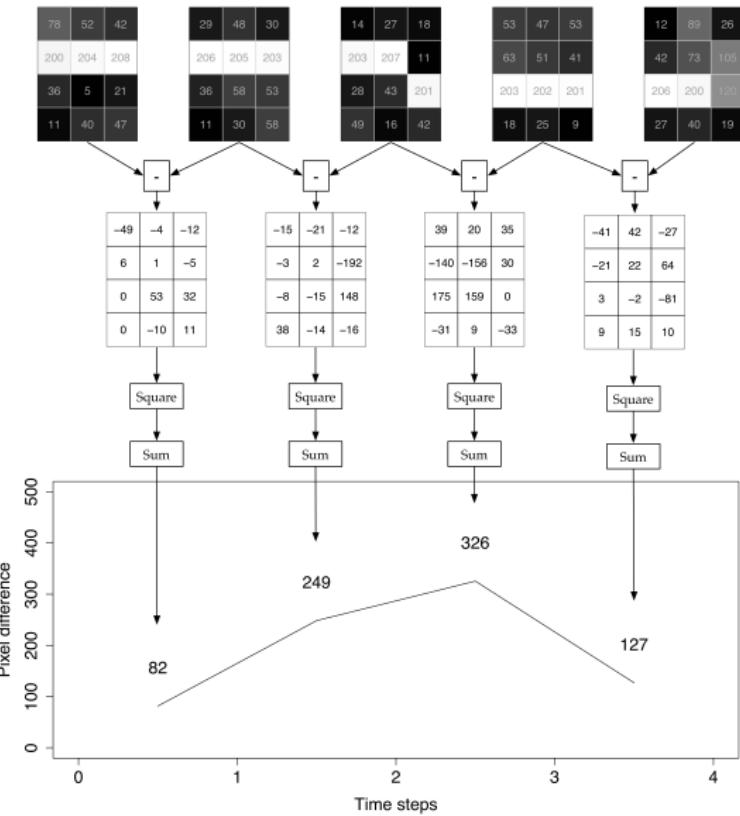


# Pixel Difference (PD)

- PD is usually calculated on uninterpolated (probe-return) ultrasound data (a) as opposed to interpolated (human-readable) data (b).



# Pixel Difference (PD)



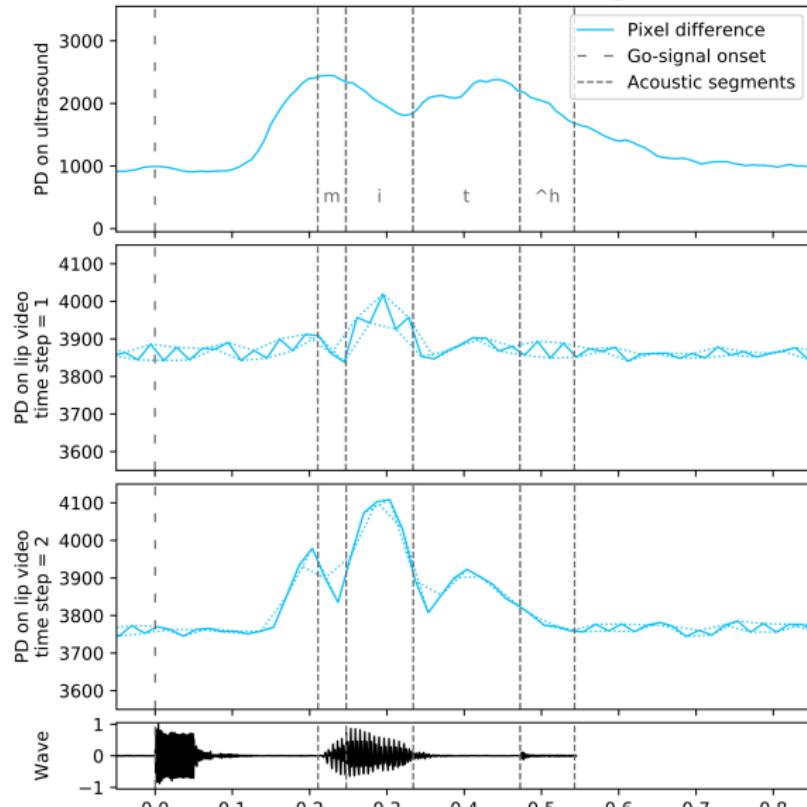
## Introduction: The how

- ▶ de-interlaced video and the zigzag: time steps
- ▶ splines and the sparseness of the data
- ▶ PD on ultrasound and time resolution
- ▶ Choosing a metric

# PD on de-interlaced videos

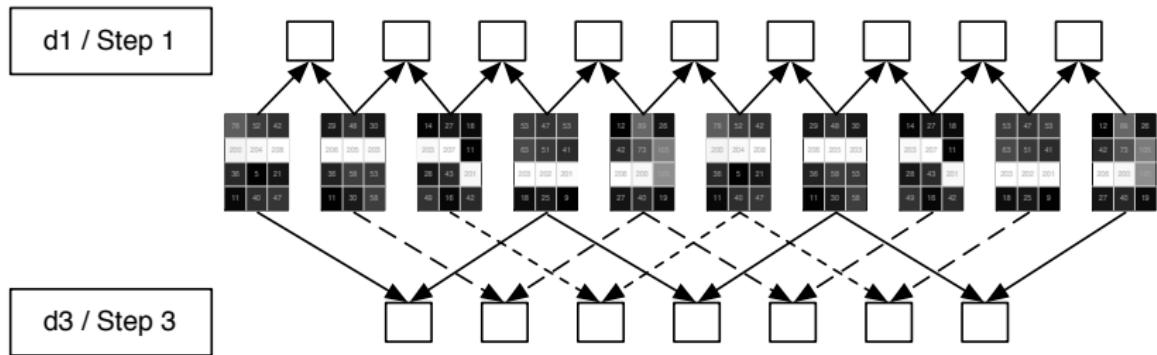
Lip video with camera attached to the ultrasound helmet.

De-interlaced at 59.94 fps.



# PD on de-interlaced videos

Taking a different time step:



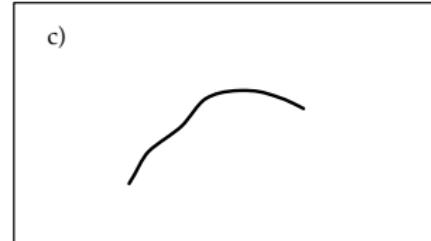
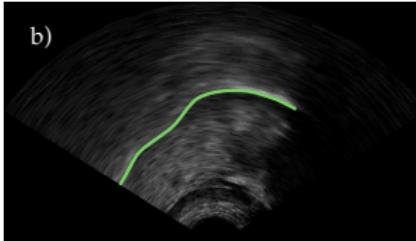
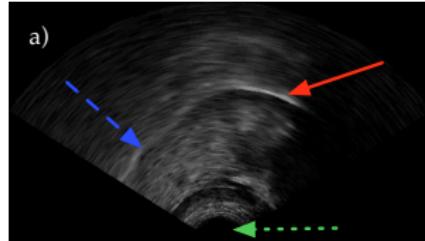
# Tongue splines and problems from sparseness

## Raw ultrasound:

- ▶ Typically 63x406 pixels per frame.
- ▶ Individual pixel's fluctuations get averaged out.

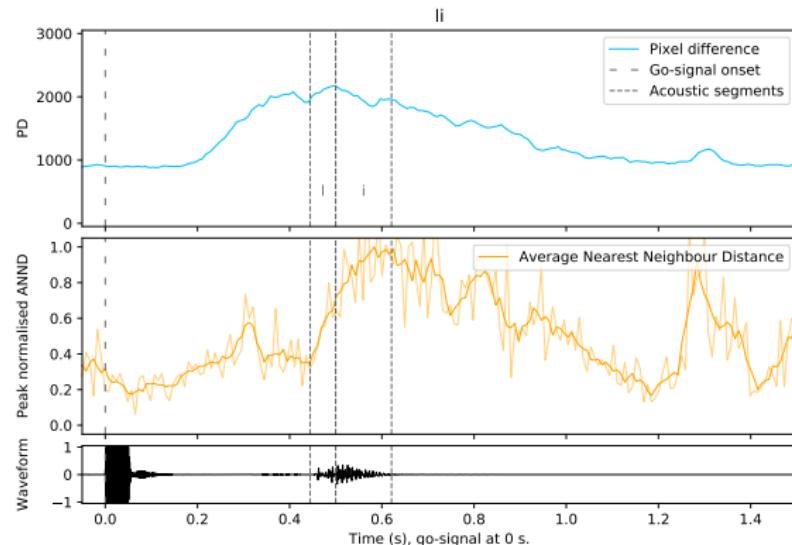
## Tongue splines:

- ▶ Typically control points per frame.
- ▶ Individual point's fluctuations may end up driving the data.



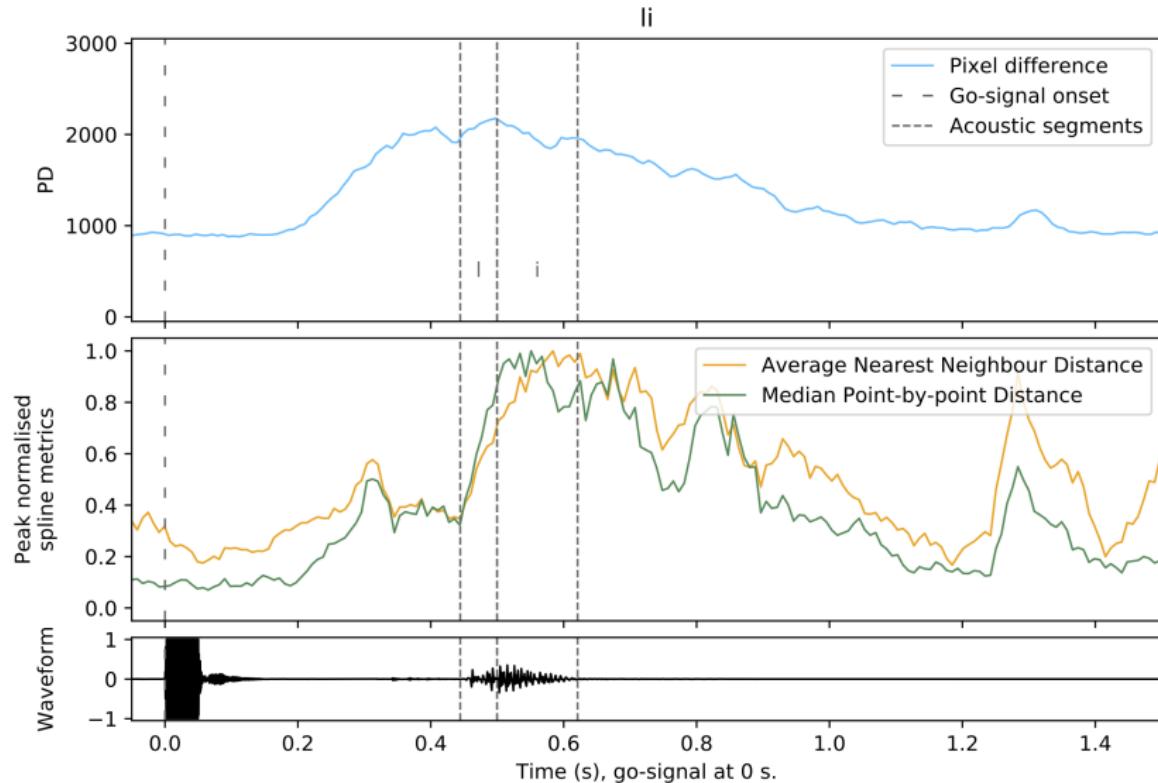
# Tongue splines and problems from sparseness

- ▶ Longer time step and averaging produce better results, but still with limits.
- ▶ Here and in the next slide ANND and MPBPD have been calculated with time step 3 and smoothed with a moving average filter with a 5 frame window.



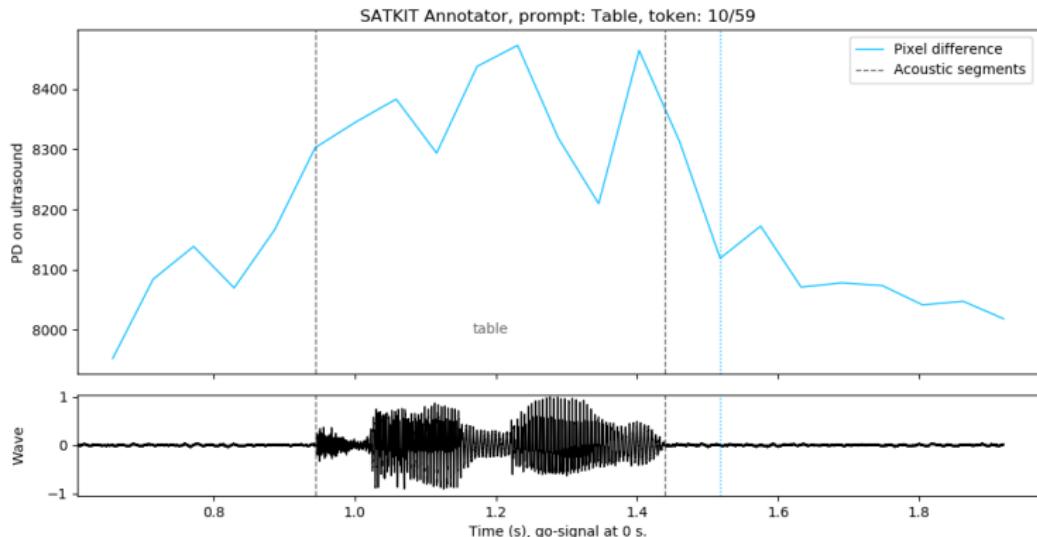
# Tongue splines and problems from sparseness

- ▶ Choice of metric can help, but not with everything.

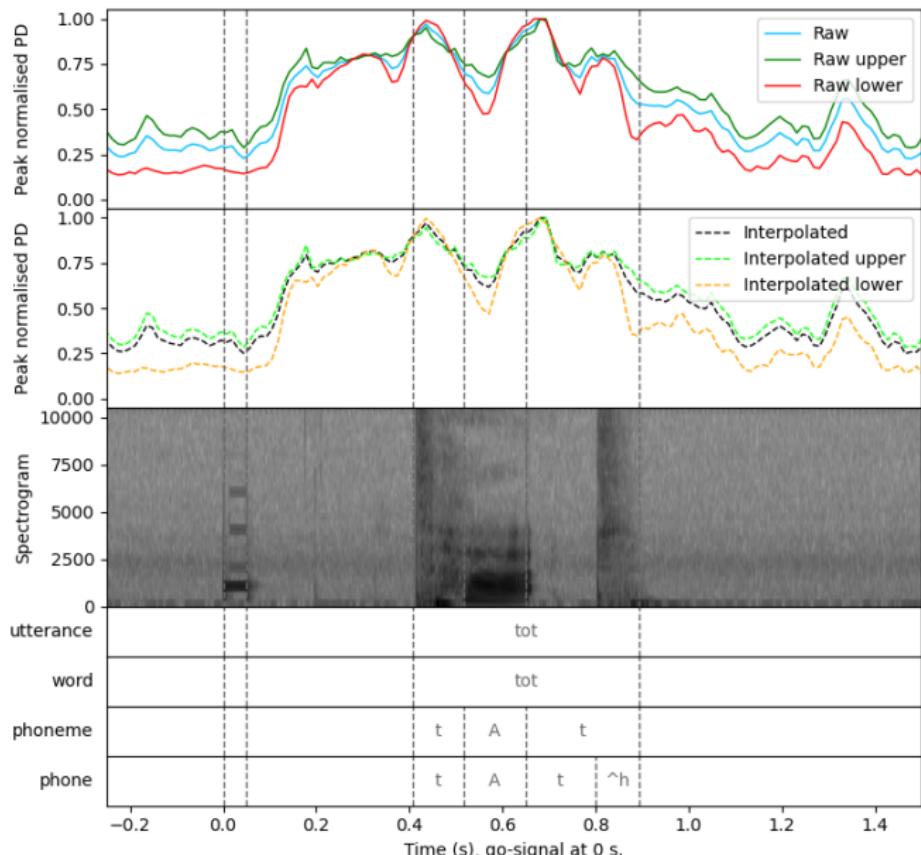


# 3D/4D ultrasound

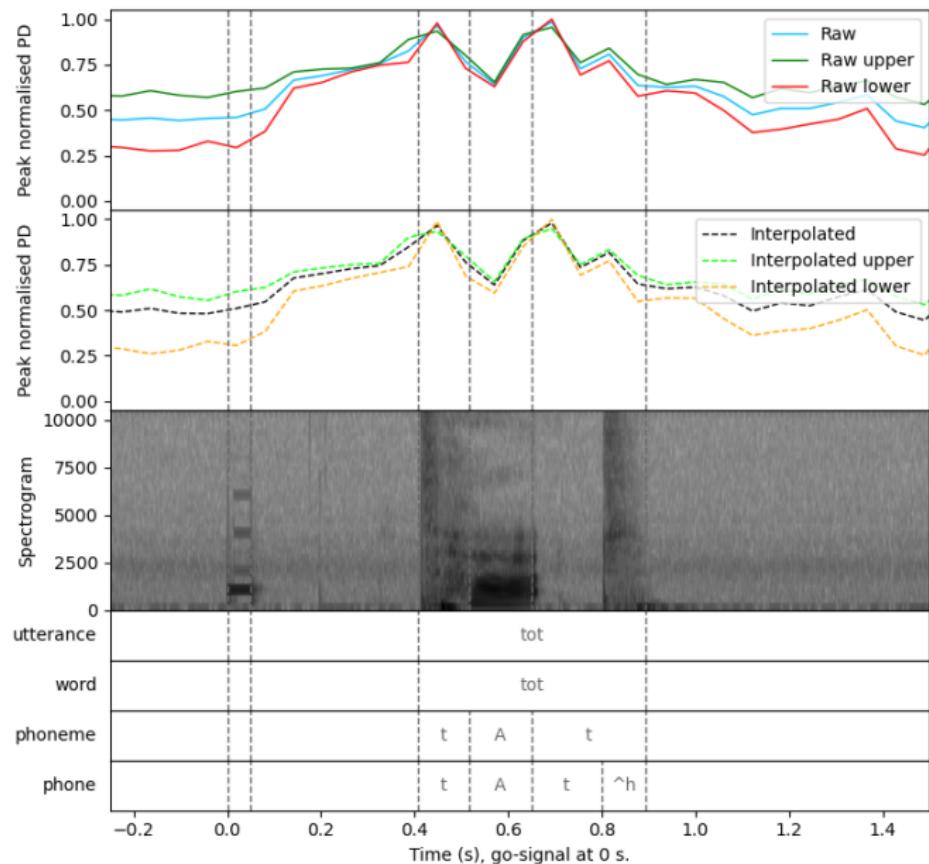
- ▶ Capturing a 3D frame takes a lot longer and we only have access to interpolated data.
- ▶ The images are always interpolated.
- ▶ In analysis even on good (lucky) samples onset and gesture recognition becomes difficult.



# PD on Raw vs Interpolated 2D data



# PD on data with artificially lowered frame rate



## In the works: Choosing the metric for PD

- ▶ PD has so far usually been calculated as the Euclidean distance or  $l_2$ -norm.
- ▶ We've recently been looking at principled ways of selecting the norm for a given data source – such as 2D ultrasound – from the different  $l_p$ -norms where  $p \in ]0, \inf[$ .
- ▶ It looks like the optimal norm for 2D ultrasound is  $l_1$  (or close to it):

$$l_1(t + 0.5) = \sum_{i,j} |x(i, j, t + 1) - x(i, j, t)|$$

## So how about MRI then?

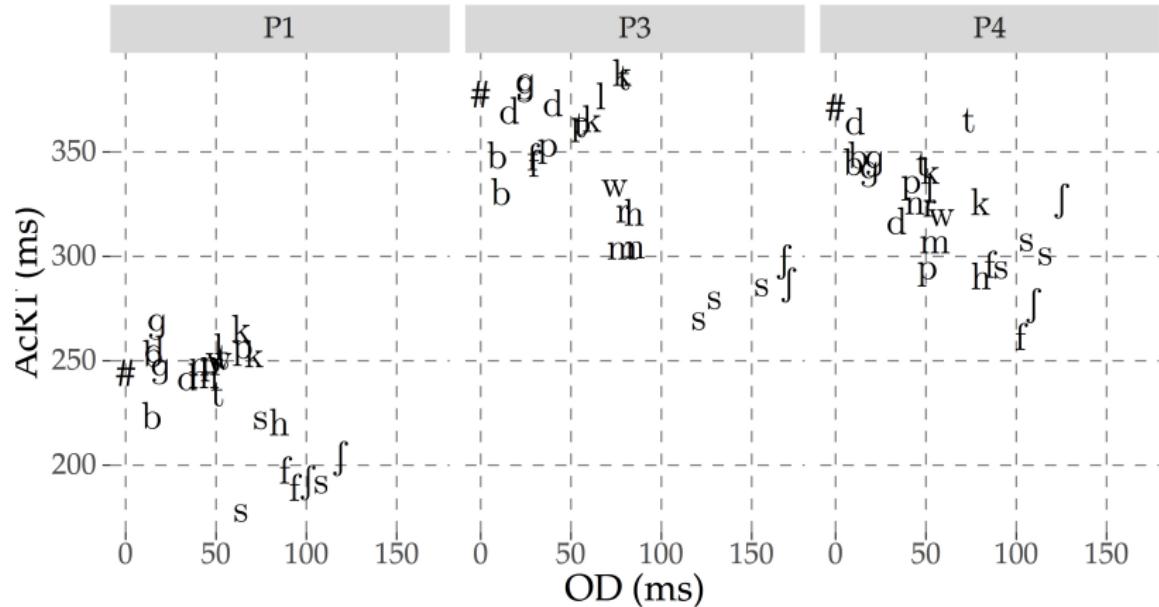
- ▶ Frame rate can be a problem.
- ▶ If there are systematic changes frame-to-frame caused by the imaging and reconstruction these may show up in PD analysis.
- ▶ Best way to get ahead with using PD for analysis would be to get a small pilot sample and run the basic version on it:  $l_2$  or  $l_1$ -norm, time step = 1, no smoothing.
- ▶ Apply larger time steps and smoothing if needed.
- ▶ Test different norms and/or look to different metrics all together.

## References

- Palo, P. (2019). *Measuring Pre-Speech Articulation*. PhD thesis, Queen Margaret University, Edinburgh.
- Rastle, K., Harrington, J. M., Croot, K. P., and Coltheart, M. (2005). Characterizing the Motor Execution Stage of Speech Production: Consonantal Effects on Delayed Naming Latency and Onset Duration. *Journal of Experimental Psychology: Human Perception and Performance*, 31(5):1083–1095.

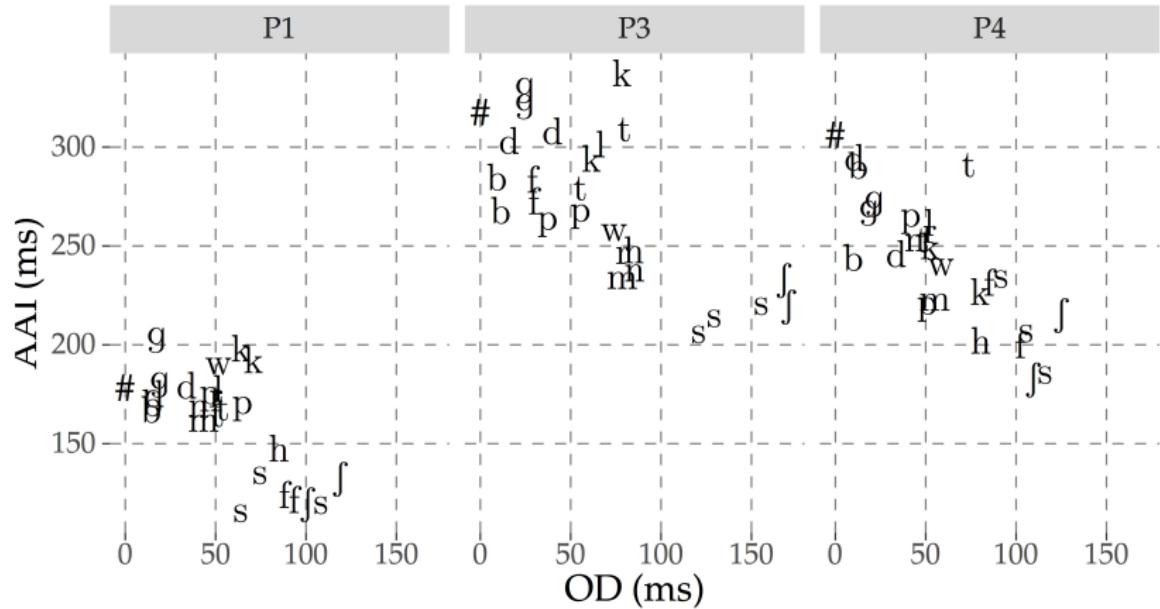
# Extra material

# Delayed naming results: Acoustics



Medianised within participant, over several repetitions and over the vowels /a,i,ɔ/. Over all analysable n = 1386: 439 from P1, 672 from P3, and 275 from P4.

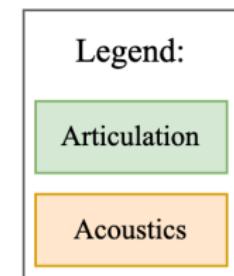
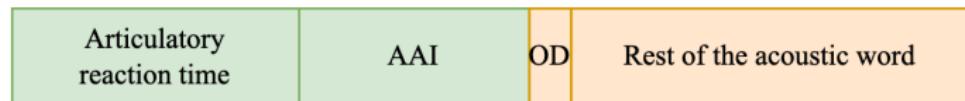
# Delayed naming results: Articulatory to Acoustic Interval



Medianised within participant, over several repetitions and over the vowels /a,i,ɔ/. Over all analysable n = 1386: 439 from P1, 672 from P3, and 275 from P4.

# Theory: Effect of OD on AAI

- ▶ As the Onset Duration (OD) gets longer, Articulatory to Acoustic Interval (AAI) shortens.
- ▶ First three lines represent individual utterances, final line is a conceptual model of the effect of continuously lengthening OD.6



AAI as a function of OD

# Theory: Effect of articulatory rate on AAI

- If we keep the utterance content constant but vary articulation rate, all parts (AAI, OD, and acoustic word) get longer as articulation rate goes down.

