

Assessing midsagittal tongue contours in polar coordinates using generalised additive (mixed) models

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1 Introduction

Since the publication of the seminal paper by Davidson (2006), statistical modelling of whole tongue contours obtained with ultrasound imaging has been dominated by the use of Smoothing Splines Analysis of Variance (SSANOVA, Gu 2013). These models have greatly advanced our understanding of tongue articulation and speech modelling. On the other hand, a variety of research disciplines is witnessing an increased use of Generalised Additive Models (GAMs) and their mixed-effects counterpart (GAMMs, Wood 2006), especially when dealing with complex data. GAMs have been increasingly adopted in linguistics as a means to model dynamic speech data. This paper introduces an implementation of GAMs with tongue contours using polar coordinates. The use of polar GAMs is illustrated with ultrasound tongue imaging data comparing voiceless and voiced stops. The R package `rticulate` has been developed to facilitate the use of the model, and it is briefly introduced here.

1.1 Ultrasound tongue imaging

Ultrasound imaging is a non-invasive technique for obtaining an image of internal organs and other body tissues. 2D ultrasound imaging has been successfully used for imaging sections of the tongue surface (for a review and applications in field settings, see Gick 2002 and Lulich et al. 2018). An image of the (2D) tongue surface can be obtained by placing the transducer in contact with the sub-mental triangle (the area under the chin), aligned either with the mid-sagittal or the coronal plane. The ultrasonic waves propagate from the transducer in a radial fashion through the aperture of the mandible and get reflected when they hit the air above the tongue surface. This ‘echo’ is captured by the transducer and translated into an image like the one shown in Figure 1.

1.2 Generalised Additive models

Generalised additive models, or GAMs, are a more general form of non-parametric modelling that allows fitting non-linear as well as linear effects, and combine properties of linear and additive modelling (Hastie & Tibshirani, 1986). GAMs are built with smoothing splines (like SSANOVA, see Helwig & Ma 2016), which are defined piecewise with a set (the *basis*) of polynomial functions (the *basis functions*). When fitting GAMs, the smoothing splines try to maximise the fit to the data while being constrained by a smoothing penalty (usually estimated from the data itself). Such penalisation constitutes a guard against overfitting. GAMs

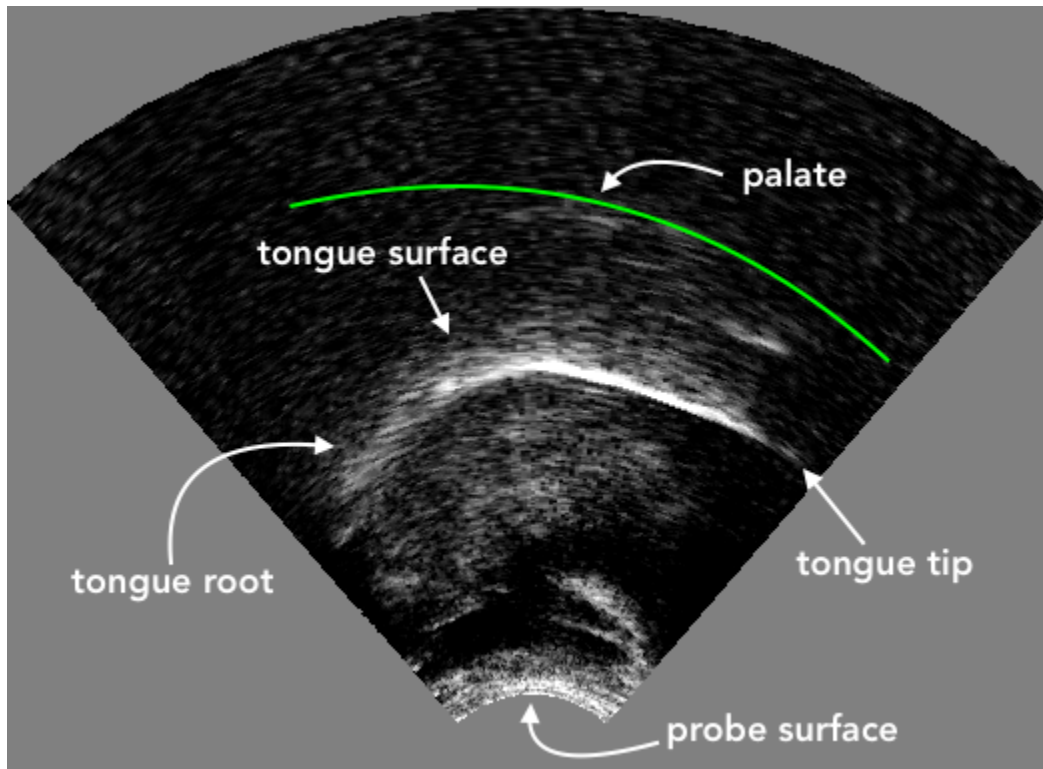


Figure 1: An ultrasound image showing a mid-sagittal view of the tongue. The white curved stripe in the image indicates where the ultrasonic waves have been reflected by the air above the tongue. The tongue surface corresponds to the lower edge of the white stripe. In this image, the tongue tip is located on the right. The green curve approximates the location of the palate.

are thus powerful and flexible models that can deal with non-linear data efficiently. Moreover, GAMs have a mixed-effect counterpart, Generalised Additive Mixed Models (GAMMs), in which random effects can be included (for a technical introduction to GAM(M)s, see Zuur (2012) and Wood (2017)). GAMs can offer relief from issues of autocorrelation between points of the contour (given that points close to each other are not independent from one another). For example, GAMs can fit separate smooths to individual contours, or a first-order autoregression model can be included which tries to account for the autocorrelation between each point in the contour and the one following it. Tongue contours obtained from ultrasound imaging lend themselves to be efficiently modelled using GAM(M)s.

1.3 Polar coordinates

Mielke (2015) and Heyne & Derrick (2015b,a) have shown that using polar coordinates of tongue contours rather than cartesian coordinates brings several benefits, among which reduced variance at the contour edges. Points in a polar coordinate system are defined by pairs of radial and angular values. The point is describes with a radius, which corresponds to the radial distance from the origin, and the angle from the reference radius. Tongue contours, due to their shape, tend to have increasing slope at the left and right edges, in certain cases tending to become almost completely vertical. The almost verticality of the contours has the effect of increasing the variance of the fitted contours (and hence increased confidence intervals), and in some cases it can even generate uninterpretable curves.

This issue is illustrated in Figure 2. The x and y axes are the x and y cartesian coordinates in millimeters. The plot shows LOESS smooths superimposed on the points of the individual tongue contours of an Italian speaker (IT01, see Section 2.1). These contours refer to the mid-sagittal shape of the tongue during the closure of four consonants (/t, d, k, g/) preceded by one of three vowels (/a, o, u/). The tip of the tongue is on the right-end side of each panel. Focussing on the smooths, it can be noticed that the smooths in the contexts of the vowel /u/ diverge substantially from the true contours (as inferred by the points). In the contexts of velar consonants and the other two vowels, one could say that the back/root of the tongue is somewhat flatted out relative to the actual contours. These artefacts of smoothing happen because, especially in the right-edge of these particular contours, the slope of the curve increases in such a way that at times the curve bends under itself (see for example the context /ug/, when x is between -30 and -20). Since those points on the bend share the x value, the smooth just averages across the y values of those points.

Figure 3 shows a better way of representing individual tongue contours. In these plots, the points of each contour are connected sequentially by a line, rather than smoothed over. The parts in which the contours bends over are kept and visualised correctly

These figures illustrate that using cartesian coordinates for modelling can introduce smoothing artefacts which in turn can negatively affect the model output. When tongue contours are expressed with polar coordinates, on the other hand, the variance is reduced and the fitted contours generally reflect more closely the underlying tongue shape. Mielke has implemented a series of R (R Core Team, 2018) functions for fitting polar SSANOVAs to tongue contours. While model fitting is achieved using polar coordinates, plotting of the model output is subsequently obtained by reconvertng the coordinates to cartesian. The method introduce in this paper is based on Mielke’s implementation applied to GAMs.

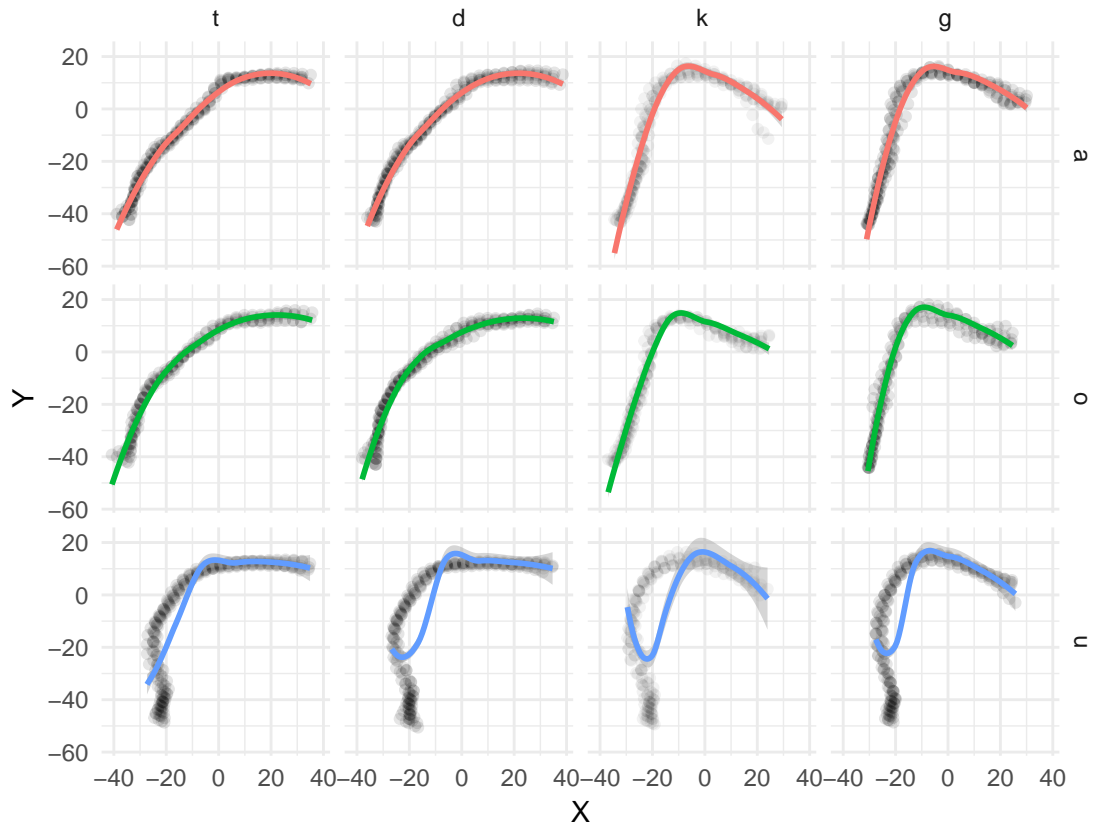


Figure 2: Estimated tongue contours of IT01 depending on C2 place, vowel and C2 voicing.

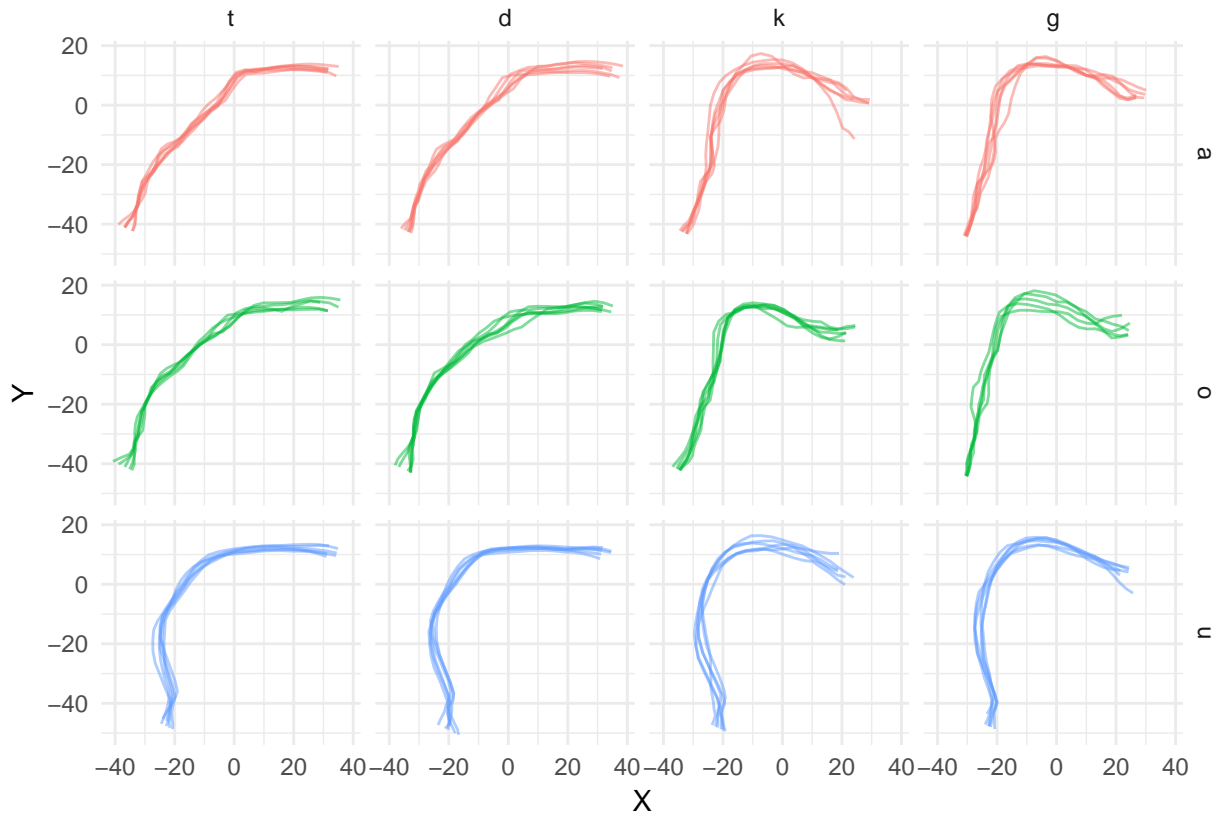


Figure 3: Estimated tongue contours of IT01 depending on C2 place, vowel and C2 voicing.

2 Polar GAM(M)s

Having shown the benefits of using GAMMs with dynamic data and polar coordinates, polar GAMMs for modelling tongue contours are introduced here. Polar GAMMs are GAMMs fitted to tongue contours using polar coordinates. As with SSANOVA, the coordinates of the fitted contours are converted to cartesian coordinates for plotting. A polar GAM is constructed as follows: the radius coordinates is the outcome variable, a smooth term over the angular coordinates is the predictor. The smooth term enables modelling the non-linearities of the contours. Predictors such as consonant or vowel type, or speech rate, can be specified in the model. The predicted polar coordinates that are returned by the model can then be converted to cartesian coordinates using the cartesian coordinate of the origin that defines the polar system. The polar origin is either known or estimated from the data, depending on the ultrasonic system used.

To illustrate the use of polar GAMs, an example will given in the following sections. The main properties of the R package `rticulate` will also be discussed in relation to the experiment. The function `polar_gam()` accepts cartesian coordinates, which are converted into polar using a user specified origin or the origin estimated from the data. The GAM is fitted on the polar coordinates and the predicted values are converted back to cartesian using the same origin for plotting.

2.1 Data collection and processing

Synchronised audio and ultrasound tongue imaging data have been recorded from 4 speakers of Italian. An Articulate Instruments LtdTM set-up was used for this study (??). The ultrasonic data was collected through a TELEMED Echo Blaster 128 unit with a TELEMED C3.5/20/128Z-3 ultrasonic transducer (20mm radius, 2-4 MHz). A synchronisation unit (P-Stretch) was plugged into the Echo Blaster unit and used for automatic audio/ultrasound synchronisation. A FocusRight Scarlett Solo pre-amplifier and a Movo LV4-O2 Lavalier microphone were used for audio recording. The acquisition of the ultrasonic and audio signals was achieved with the software Articulate Assistant Advanced (AAA, v2.17.2) running on a Hewlett-Packard ProBook 6750b laptop with Microsoft Windows 7. Stabilisation of the ultrasonic transducer was ensured by using a headset produced by Articulate Instruments LtdTM (2008).

Before the reading task, the participant's occlusal plane was obtained using a bite plate (Scobbie et al., 2011). The participants read nonce words embedded in the frame sentence *Dico ____ lentamente* 'I say ____ slowly'. The words follow the structure $C_1V_1C_2V_2$, where $C_1 = /p/$, $V_1 = /a, o, u/$, $C_2 = /t, d, k, g/$, and $V_2 = V_1$. Each speaker repeated the stimuli six times.

Spline curves were fitted to the visible tongue contours using the AAA automatic tracking function. Manual correction was applied in those cases that showed clear tracking errors. The time of maximum tongue displacement within consonant closure was then calculated in AAA following the method in Strycharczuk & Scobbie (2015), described in what follows. A fan-like frame consisting of 42 equidistant radial lines was used as the coordinate system. The origin of the 42 fan-lines coincides with the centre of the ultrasonic probe, such that each fan-line is parallel to the direction of the ultrasonic signal. Tongue displacement was thus

calculated as the displacement of the fitted splines along the fan-line vectors. The time of maximum tongue displacement was the time of greater displacement along the vector that showed the greatest standard deviation. The vector search area was restricted to the portion of the splines corresponding to the tongue tip for coronal consonants, and to the portion corresponding to the tongue dorsum for velar consonants.

The cartesian coordinates of the tongue contours were extracted from the ultrasonic data at the time of maximum tongue displacement (always within C2 closure). The contours were subsequently normalised within speaker by applying offsetting and rotation relative to the participant’s occlusal plane (Scobbie et al., 2011). The dataset is thus constituted by x and y coordinates of the tongue contours that define respectively the horizontal and vertical axis. The horizontal plane is parallel to the speaker’s occlusal plane.

2.2 Fitting a polar GAM

GAMMs can be fitted in R with the `gam()` function from package `mgcv` (Wood, 2011, 2017). `bam()` is a more efficient function when the datasets has several hundreds observations. The package `rticulate` has been developed as a wrapper of the `bam()` function to be used with tongue contours. The special function `polar_gam()` can fit any specified GAM model to tongue contours coordinates, using the same syntax of `mgcv`. The function accepts tongue contours either in cartesian or polar coordinates. In the first case, the coordinates can be transformed into polar before fitting. The function `plot_polar_smooths()`, used for plotting the estimated contours, converts the coordinates back into cartesian.

A GAM in R can be specified with a formula that uses the same syntax of `lme4`, a commonly used package for linear mixed-effects models (Bates et al., 2015). The `mgcv` package allows to specify smoothing spline terms with the function `s()`. This function takes the term along which a spline is created (for example, a time series, or x -coordinates). Within `s()` the user can choose, among other arguments, what kind of spline to use, and the grouping factor (namely, the factor with the levels to be compared). For a more in-depth introduction to GAM(M)s in R targeted to linguists, see Sóskuthy (2017) and Wieling (2017).

Due to differences in the placement of the probe and the speaker’s anatomy, different portions of the tongue are likely to be imaged across speakers. For this reason, it is recommended to fit separate models for each participant, rather than aggregate all of the data in a single model.

As means of illustration, the following paragraphs will show how to fit a polar GAM with data from one of the 4 Italian speakers.

We can start from a simple model in which we test the effect of C2 place, vowel, and voicing on tongue contours. Modelling different contours for each combination of the three predictors can be achieved with the `by` argument in the difference smooth function and including the related parametric term. `vc_voicing` is an ordered factor which specifies for each contour the combination of C2 place, vowel, and voicing. The following code fits the specified model to the contour data of IT01. When running the code, the coordinates of the estimated origin used for the conversion to polar coordinates are returned. The author can optionally specify those manually, the contours are not in a fan-like system (like the data exported from AAA).

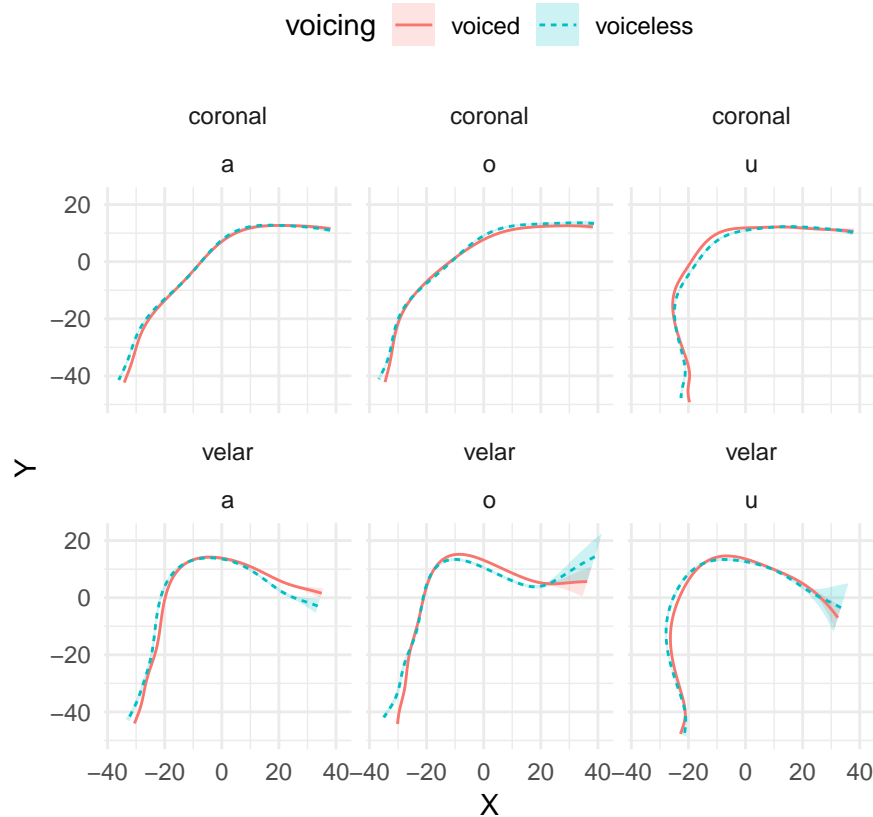


Figure 4: Estimated tongue contours of IT01 depending on C2 place, vowel and C2 voicing.

```
## The origin is x = 14.3900999664996, y = -65.2314226131983.
```

The function `plot_polar_smooths()` can be used to plot the estimated contours. The shaded areas around the estimated contours are 95% confidence intervals. Note that, differently from SSANOVA, statistical significance can't be assessed from the overlapping (or lack thereof) of the confidence intervals.

One way of assessing significance is to compare the ML score of the full model against one without the relevant predictor, using the function `compareML()` from the `itsadug` package. Both the parametric term and the difference smooth need to be removed in the null model.

```
## The origin is x = 14.3900999664996, y = -65.2314226131983.
```

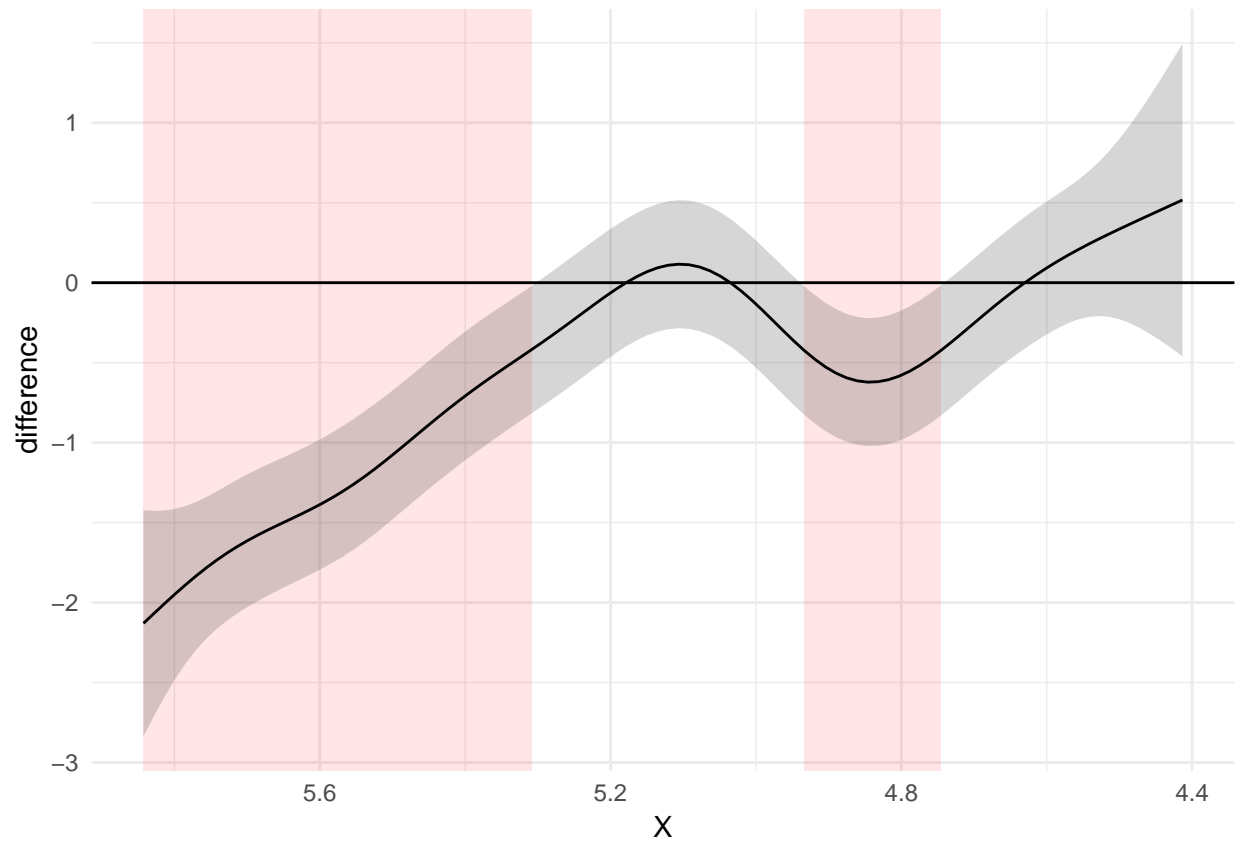
```
## it01_gam_0: Y ~ s(X)
##
## it01_gam: Y ~ vc_voicing + s(X) + s(X, by = vc_voicing)
##
## Chi-square test of ML scores
## -----
##           Model      Score Edf Difference      Df  p.value Sig.
## 1 it01_gam_0 12395.227    3
## 2  it01_gam  7423.356   36  4971.871 33.000 < 2e-16 ***
```

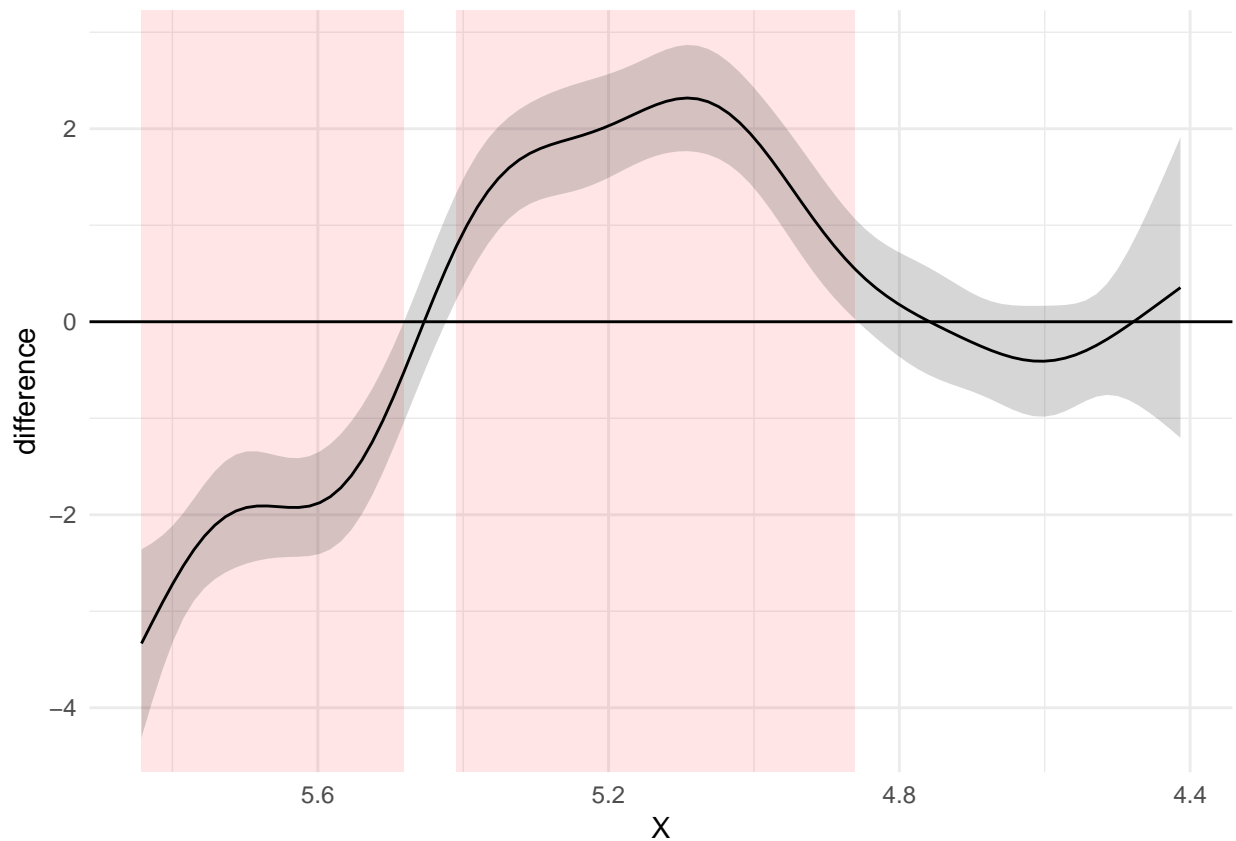


```
##
```

```
## AIC difference: 10258.65, model it01_gam has lower AIC.
```

To check which part of the contour differs among conditions, the method recommended in Sós-kuthy (2017) is to plot the difference smooth and check the confidence interval. The parts of confidence interval that don't include 0 indicate that the difference between contours in that part is significant.





3 Comparing tongue contours in voiceless and voiced stops

Mid-sagittal tongue contours at maximum tongue displacement of voiceless and voiced stops have been compared using polar GAMs. The plots in ... show that there is an appreciable degree of variation across speakers and phonological contexts. In some speakers and contexts, the tongue root (on the left of the tongue contour) is more advanced in the voiced stops than in the voiceless stops. The magnitude of the difference is about 2 millimetres, and it is more common when C2 is coronal and the vowel is /a/. Kirkham & Nance (2017) find that the tongue root in +ATR vowels is on average 4 millimetres more advanced than the respective -ATR vowels. Given this estimate, a 2 millimetres difference seems appropriate, or two very different vowels would end up before voiceless vs. voiced stops (cf. with phonologisation of ATR depending on voicing ...).

```
## The origin is x = 14.3900999664996, y = -65.2314226131983.
## The origin is x = 14.3900999664996, y = -65.2314226131983.

## it01_gam_ar_0: Y ~ s(X)
##
## it01_gam_ar: Y ~ vc_voicing + s(X) + s(X, by = vc_voicing)
##
```

```

## Chi-square test of ML scores
## -----
##           Model      Score Edf Difference      Df  p.value Sig.
## 1 it01_gam_ar_0 5972.86   3
## 2  it01_gam_ar 3293.08  36  2679.780 33.000  < 2e-16  ***
##
## AIC difference: 5636.46, model it01_gam_ar has lower AIC.

## Warning in compareML(it01_gam_ar_0, it01_gam_ar): AIC might not be
## reliable, as an AR1 model is included (rho1 = 0.894493, rho2 = 0.894493).

## The origin is x = 22.3502276497439, y = -63.9479946349349.
## The origin is x = 22.3502276497439, y = -63.9479946349349.
## The origin is x = 22.3502276497439, y = -63.9479946349349.

## it02_gam_ar_0: Y ~ s(X)
##
## it02_gam_ar: Y ~ vc_voicing + s(X) + s(X, by = vc_voicing)
##
## Chi-square test of ML scores
## -----
##           Model      Score Edf Difference      Df  p.value Sig.
## 1 it02_gam_ar_0 4718.543   3
## 2  it02_gam_ar 3394.247  36  1324.296 33.000  < 2e-16  ***
##
## AIC difference: 2823.71, model it02_gam_ar has lower AIC.

## Warning in compareML(it02_gam_ar_0, it02_gam_ar): AIC might not be
## reliable, as an AR1 model is included (rho1 = 0.883642, rho2 = 0.883642).

## The origin is x = 18.8671533068358, y = -54.2069374500317.
## The origin is x = 18.8671533068358, y = -54.2069374500317.
## The origin is x = 18.8671533068358, y = -54.2069374500317.

## it03_gam_ar_0: Y ~ s(X)
##
## it03_gam_ar: Y ~ vc_voicing + s(X) + s(X, by = vc_voicing)
##
## Chi-square test of ML scores
## -----
##           Model      Score Edf Difference      Df  p.value Sig.
## 1 it03_gam_ar_0 3904.872   3
## 2  it03_gam_ar 2205.682  36  1699.190 33.000  < 2e-16  ***
##
## AIC difference: 3596.78, model it03_gam_ar has lower AIC.

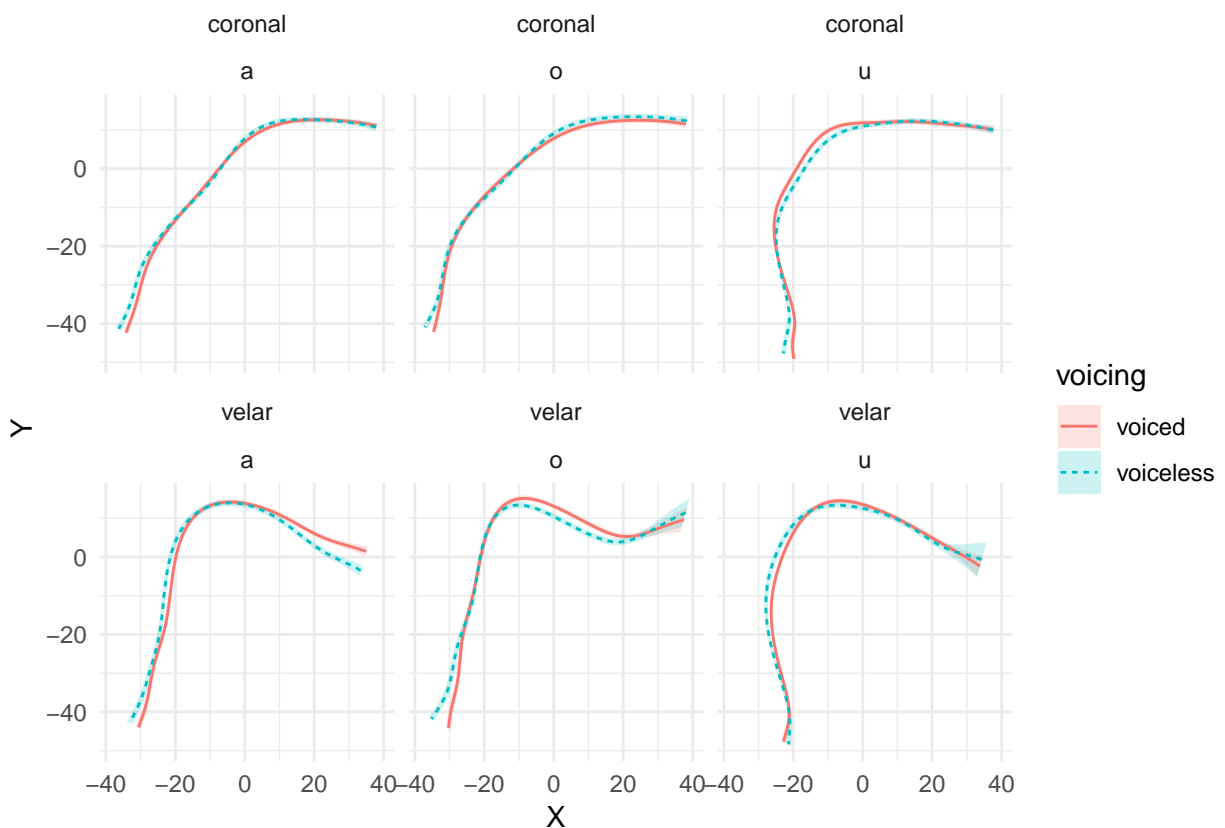
```

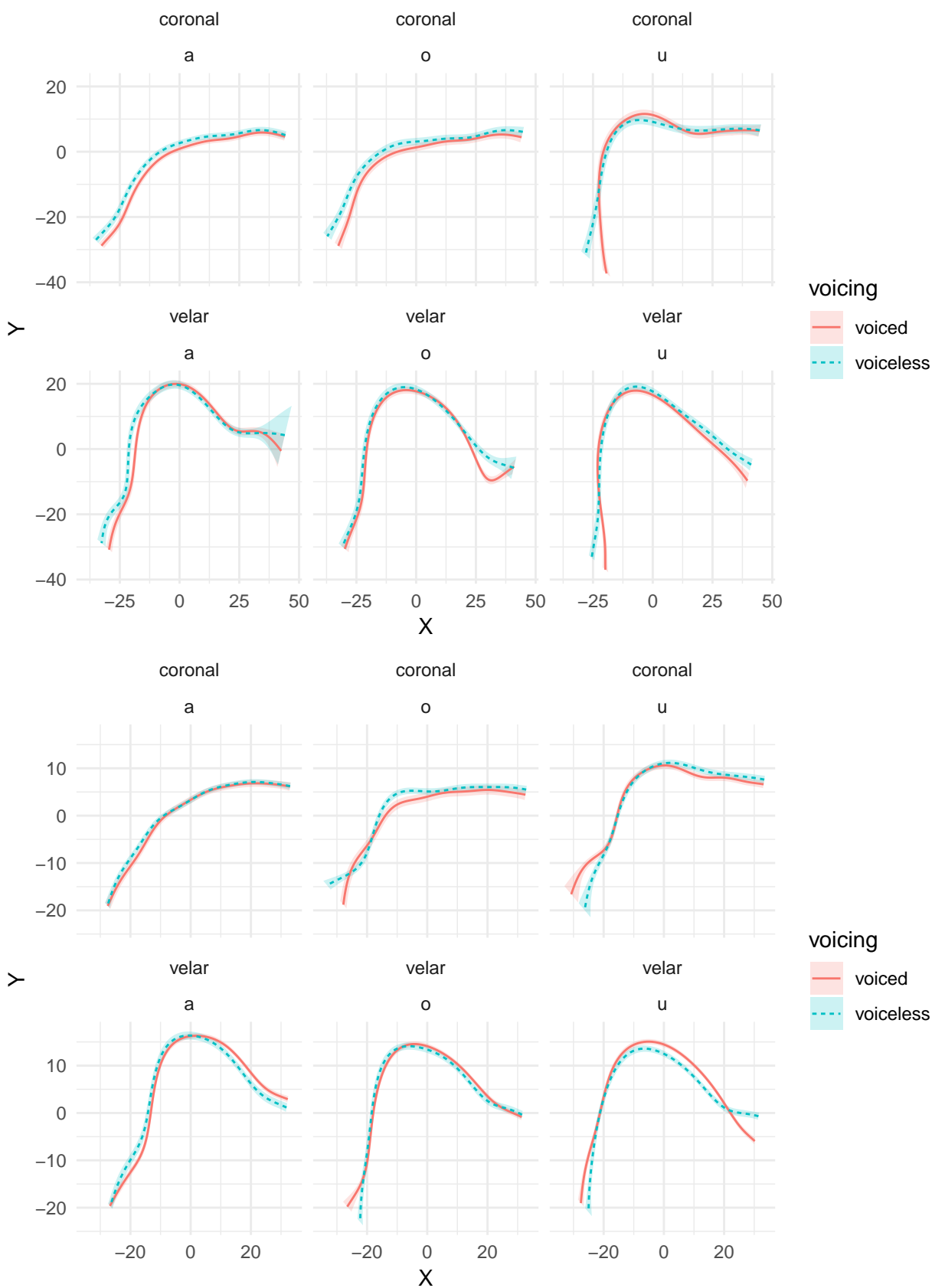
```
## Warning in compareML(it03_gam_ar_0, it03_gam_ar): AIC might not be
## reliable, as an AR1 model is included (rho1 = 0.887306, rho2 = 0.887306).

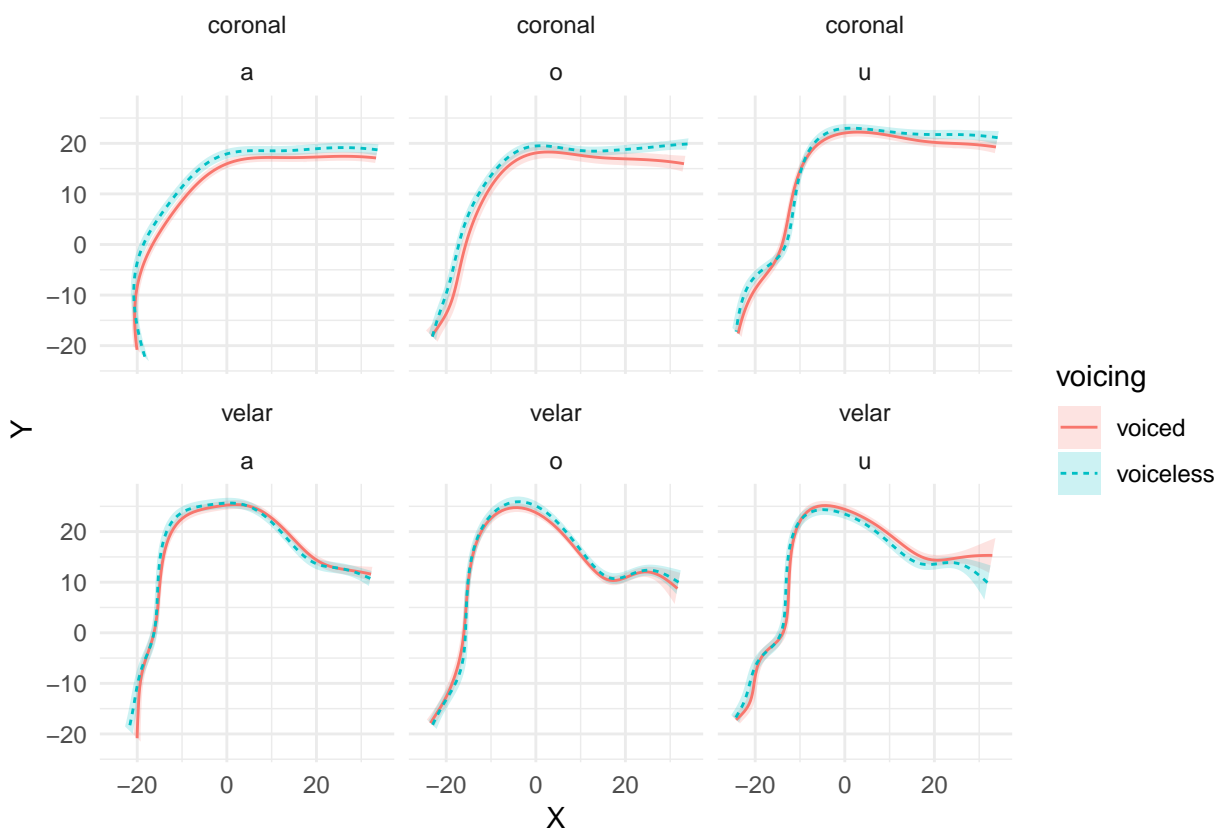
## The origin is x = 18.8671244233962, y = -54.207062619097.
## The origin is x = 18.8671244233962, y = -54.207062619097.
## The origin is x = 18.8671244233962, y = -54.207062619097.

## it04_gam_ar_0: Y ~ s(X)
##
## it04_gam_ar: Y ~ vc_voicing + s(X) + s(X, by = vc_voicing)
##
## Chi-square test of ML scores
## -----
##           Model      Score Edf Difference      Df  p.value Sig.
## 1 it04_gam_ar_0 4557.608   3
## 2  it04_gam_ar 3218.615  36   1338.993 33.000  < 2e-16  ***
##
## AIC difference: 2930.64, model it04_gam_ar has lower AIC.

## Warning in compareML(it04_gam_ar_0, it04_gam_ar): AIC might not be
## reliable, as an AR1 model is included (rho1 = 0.924528, rho2 = 0.924528).
```







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