Learning and adaptation of a tongue shape model with missing data

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We consider a realistic, data-driven model of the tongue shape, in particular its midsagittal contour.

Applications: talking heads, articulatory synthesis and inversion, tracking in ultrasound and MRI, and reconstructing the tongue contour in articulatory databases such as MOCHA.

Landmark-based models use as control parameters the location on the tongue contour of a fixed number of fleshpoints (landmarks), given which the entire tongue shape is reconstructed. This is a low-dimensional model of the tongue contour.

We consider two fundamental problems:

- **Training** the model for a speaker, given a large dataset of contours.
- **Adapting** the model to a new speaker, given a few contours.

In this paper, we solve both problems when there is missing data.
Reconstructing EMA/X-ray microbeam (Qin et al., ’10)

Our original motivation: reconstruct the tongue contour in EMA/X-ray microbeam articulatory databases by adapting a tongue model constructed for a reference speaker.
The training problem: learn a predictive model $f$ of the full tongue contour for a given speaker given many full contours from it.
Predictive model of the tongue contour (cont.)

Given the 2D locations of $K$ landmarks located on the tongue contour ($x$), reconstruct the entire contour ($y$), represented by $P$ 2D points.

We can obtain full contours from ultrasound recordings (semiautomatic segmentation process).
Learn a predictive mapping $f$ in order to reconstruct the full tongue contour given only a few landmarks, from a dataset $\{(x_n, y_n)\}_{n=1}^{\mathcal{N}}$ containing many contours.

**Radial basis function (RBF) network:** $f(x) = W \Phi(x) + w$

$M$ Gaussian basis functions $\phi_m(x) = \exp\left(-\frac{1}{2} \|x - \mu_m\|/\sigma^2\right)$, width $\sigma$.

Minimize the following objective function given $\mathcal{N}$ contours:

$$E(f) = \sum_{n=1}^{\mathcal{N}} \|y_n - f(x_n)\|^2.$$ 

This achieves submillimetric error per contour point (below the ultrasound measurement accuracy).

It beats spline interpolation of the landmarks.
Adapting a predictive model to a new speaker (Qin et al. ’09, ’10)

The adaptation problem: adapt the predictive model $f$ to a new, target speaker given a few full contours from the latter.
We transform contours between speaker spaces with invertible linear mappings $g_x(x)$ and $g_y(y)$ constructed with 2D-wise mappings $g^i$:

$$g(x) = Ax + b$$

$$g^{-1}_y(f(g_x(x)))$$

$$g^{-1}_y(f(g_x(x)))$$

$$g_x(x) = \begin{bmatrix} A^x_1 x_1 + b^x_1 \\ \vdots \\ A^x_K x_K + b^x_K \end{bmatrix}$$

$x_1, \ldots, x_K \in \mathbb{R}^2$

and same for $g^{-1}_y(y)$.

Total $6(K + P)$ parameters ($\ll \# \text{ parameters of } f$).

We minimize the following objective function given $N$ adaptation contours using BFGS (details in paper):

$$E(A^x, b^x, C^y, d^y) = \sum_{n=1}^{N} \left\| y_n - g^{-1}_y(f(g_x(x_n))) \right\|^2$$

This requires no correspondences (i.e., the adaptation contours need not match any sound of the reference).
Adapting a predictive model to a new speaker (cont.)

Contours before adaptation

Contours after adaptation
(not all contours shown, to avoid clutter)
Training and adaptation with missing data

Missing data in ultrasound (incomplete contours) caused by:

- Noise and shadows occlude portions of the contour.
- Back/tip of tongue may exit window of visibility of the probe.
- Tongue surfaces disappear if parallel to the probe.
- Errors in (manual or automatic) segmentation of the tongue contour.

![Ultrasound images showing midsagittal tongue contour, hyoid bone shadow (back), teeth shadow (front)](image-url)
We cannot afford to discard incomplete contours:

- Wasteful (recording and segmentation are costly and cumbersome).
- Can severely reduce the number of complete contours available, particularly in the adaptation setting.

The tongue contours have implicit temporal and spatial redundancy.

Assume now we are given a dataset of contours \( \{(x_n, y_n)\} \), each of which may contain missing points.
Training and adaptation with missing data (cont.)

Approach 1: reconstruct the missing data, the train/adapt as usual.
- Mean imputation.
- Spline imputation.

Sample contours with missing runs

Mean and spline imputation with missing data at random/in runs
Training and adaptation with missing data (cont.)

**Approach 2:** directly train/adapt without reconstructing any missing data ("missing data deleted" technique: drop missing terms from objective):

- **Training:** $E(f) =$
  - With complete data: $\sum_{n=1}^{N} \sum_{j=1}^{2P} (y_{jn} - (f(x_n))_j)^2$.
  - With missing data: $\sum_{\text{present } n,j} (y_{jn} - (f(x_n))_j)^2$.

- **Adaptation:** $E(A^x, b^x, C^y, d^y) =$
  - With complete data: $\sum_{\text{present } n,j} (y_{jn} - (g_y^{-1}(f(g_x(x))))_j)^2$.
  - With missing data: $\sum_{\text{present } n,j} (y_{jn} - g_y^{-1}(f(g_x(x))))_j)^2$.

- **Computational cost:**
  - Both missing-data objective functions have $(1 - \rho)PN$ terms where $\rho \in [0, 1]$ is the proportion of missing data $\Rightarrow$ faster.
  - Imputation methods first reconstruct all contours (so $\rho = 0$) and then minimize $\Rightarrow$ slower, and also larger error.
Experimental results: setup

- Ultrasound database: two speakers (one male, one female) with different Scottish accents ($\approx 10\,000$ contours). We used the male speaker to obtain a reference model, which we adapted to data from the female speaker having missing values. We take $K = 3$ landmarks and $P = 24$ contour points.

- Missing patterns:
  - Missing at random (from 0% to 60% MD). representative of random ultrasound noise
  - Missing run (8 consec. points) at front/mid/back (= 33% MD). representative of shadowing and other effects

- Comparison methods:
  - Optimal baseline: many contours, no missing data.
  - Retraining a new model from scratch (disregarding the reference model $f$).
  - Mean imputation and spline imputation.
  - Direct training/adaptation without reconstructing missing data.
Experimental results (cont.)

**Missing at random pattern**, predictive error $E$ for adaptation and retraining with different amounts of missing data, as a function of the number of adaptation contours $N$.

- Adaptation beats retraining for $N < 100$ contours.
- With as few as $N = 30$ contours and up to 60% missing data, we achieve an error within 0.5 mm from the optimal baseline.
- With very few contours ($N < 30$), up to 20% missing data is still tolerated.
Missing at random pattern (60% missing data), comparing direct retraining/adaptation (blue lines) with retraining/adaptation after mean imputation (red) and spline imputation (green).

- Direct retraining/adaptation does best.
- Spline imputation does somewhat worse.
- Mean imputation does poorly.
Experimental results (cont.)

Missing runs pattern (33% missing data), comparing direct retraining/adaptation (blue lines) with retraining/adaptation after mean imputation (red) and spline imputation (green).

- Direct retraining/adaptation does best, with an error similar to the missing-at-random case.
- Spline imputation does quite worse.
- Mean imputation is off the chart.
Conclusions

❖ We have extended a landmark-based training and adaptation model of the tongue shape to deal with missing data.

❖ With significant amounts of missing data, we achieve an accuracy comparable to that using complete data, and with less computation time.

❖ No need to reconstruct the missing data.

❖ Limitation: the landmarks themselves cannot be missing.

❖ Could use to increase the temporal resolution of ultrasound by skipping scan lines (reducing the spatial resolution), thus trading off missing data in the temporal and spatial domains.

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