



Modelling similarity perception of intonation

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Introduction

Research context

- Intonation modelling
 - based on human perceptual equivalence judgements (e.g. IPO, t'Hart et al., 1990)
 - based on physical distance measures not motivated by human perception (e.g. PaintE, Möhler&Conkie, 1998)
 - goal: combine both \longrightarrow perceptual justification + automatisation
- Evaluation of Speech synthesis systems (Clark&Dusterhoff, 1999)
- Second language acquisition (Hermes, 1998)

Given Approaches

- **Physical measures:** e.g. correlation, absolute distance, RMS (Hermes, 1998), tangential and warping methods (Clark&Dusterhoff, 1999)
- **Evaluation:** e.g. correlation with human judgements derived from an ordinal scale (Hermes, 1998), so far up to 0.7.

Hypotheses and goals

- Ability of subjects to judge intonation similarity:
- (1) Identical contours are judged to be more similar than different contours
- (2) Contour judgements are consistent
- signal properties guiding the similarity judgements:
- (3) There is a measurable relation between acoustic and perceived intonation similarity

Perception of intonation similarity

Subjects

- n=24 (17 female)
- age: from 20 to 42
- trained phoneticians: 19
- musical education: 14
- German native speakers: 19

Stimuli

- delexicalised [mama:ma] stimuli (vs. top-down processing)
- generated by Mbrola (male German voice; Dutoit et al., 1996)
- relevant f0 movement on the center syllable
- onset and nucleus **durations**: 60 and 200 ms, 130 and 300 ms, and 80 and 220 ms respectively (which was judged as natural and yielded the desired prominence relation in an informal pretest)

- f0 generation:
 - target syllable: third order polynomials, coefficients drawn randomly from ranges derived from f0 stylised corpus (IMS corpus, male German voice)
 - remaining contour: cubic spline extrapolation
 - constraints: concerning f0 range and distance of subsequent values

Method

- stimuli presented pairwise to the subjects over head phones (ISI: 0.5 sec, n(pairs)=300, presented once, 30 trial blocks)
- similarity judgement by clicking in a white area on the screen, the vertical position corresponding to perceived similarity
- no scale given since:
 - there is no sequence of equidistant categories related to similarity
 - ordinal scale hard to interpret (informal pretest)
- stimulus subsets:
 - IDENT: 20 pairs of identical contours to test Hypothesis (1)
 - CONSIST: 40 triplets (pairs presented 3 times) to test Hypothesis (2)
- **removing judgement bias** by normalising the answers to [0 1], reflecting the amount of **perceived similarity**

Results

• Capability of similarity judgements



Figure 1: Left: Perceived similarity of identical vs. differing contours. **Right:** Inconsistencies (standard deviations) for repeated pair and randomly combined pair triplets.

- means of identical vs. different contour similarity judgements: 0.92 vs. 0.43, h.s. (one-tailed Welch test, p < 0.0001) \longrightarrow Hypothesis (1) confirmed
- mean inconsistencies (standard deviations) of repeated vs. random pair triplets: 0.17 vs. 0.25, h.s. (one-tailed Mann-Whitney test, p < 0.0001) \longrightarrow Hypothesis (2) confirmed
- Subjects are capable to judge intonation similarity

Relation between physical and perceptual intonation distance

• transforming similarity to distance judgements: d = 1 - s

Correlations

Table 1: Pearson r between perceived distance of intonation contours and a collection of theirphysical distances applied to raw f0 contours (in ST) and polynomial coefficients.

	contours	coefficients
Euclidean	0.40	0.38
Cityblock	0.38	0.37
Chebychev	0.47	0.38
1-Cosine	0.22	0.32
1-Correlation	0.33	0.29

- all correlations significantly different from zero (t-test, p = 0) \longrightarrow Hypothesis (3) confirmed
- but nevertheless low —> metrics in isolation not capable of predicting perceived distance

Relative weights

- grouping of the metrics by PCA loadings into four categories
 - pc_1 : non-correlation-based distances for f0 contours
 - pc_2 : non-correlation-based distances for polynomial coefficient vectors
 - pc₃: correlation-based distances (1–Cosine, 1–Correlation) of polynomial coefficient vectors
 - pc_4 : correlation-based distances of f0 contours
- linear regression using pc₁-pc₄ as predictors for distance perception and comparing the regression weights
- result: $pc_1 > pc_3 > pc_2 > pc_4$
- non-correlation-based distances of f0 contours have the highest relative influence on perceived distance

Modelling the perception of similarity

Features

- 1-Correlation of the polynomial coefficient vectors
- pairwise absolute distances between the coefficient values
- Euclidean, Chebychev, and 1–Correlation distance between the onset contours (in ST) of the target syllable
- Euclidean, Chebychev, and 1–Correlation distance between the nuclei contours of the target syllable
- dichotomous algebraic sign comparison of the slope coefficients
- absolute differences in 7 equally sized area segments between the contours
- absolute difference of number of contour maxima
- previous answer of the listener
- **Preprocessing:** orthogonalisation by PCA

Model 1: linear regression

• pairwise interaction model: $d_p = w_0 + \sum_i w_i f_i + \sum_i \sum_j w_{ij} f_i f_j$

Model 2: Two-layer feed-forward networks



Figure 2: Network Architecture







Figure 4: Activation functions $a(I_i)$. Here *logsig* is chosen.

- training:
 - modification of the weights w_{ij} in order to yield outputs d_p as close as possible to human distance judgements d
 - gradient descent backpropagation with momentum and adaptive learning rate vs. stranding in and oscillating around local optima



Figure 5: Gradient descent learning: update of weight w_j guided by local minimisation of error E (=MAE between d and d_p).

Method

- excluding data from two subjects performing very badly with respect to judgement consistency
- 10-fold cross validation

Results

 human performance: standard deviation of the judgements for repeated contour pairs (= root mean squared error RMSE assuming, that the correct answer is given by mean value)

$$RMSE_{d-triplett} = \sqrt{\frac{1}{3} \sum_{i=1}^{3} (d_i - \overline{d})^2}$$

• model performance: RMSE for each model prediction (= absolute error)

RMSE<sub>*d_p* =
$$\sqrt{(d_p - d)^2} = |d_p - d|$$</sub>



Figure 6: Human errors in terms of standard deviation of the judgement of repeated pair triplets. Absolute errors of the neural network and the regression model.

- one-way ANOVA, factor *performer* ("human" vs. "feed forward network" vs. "linear regression"): significant mean differences (p = 0.002)
- Tukey-Kramer post-hoc: only significant differences between human and the linear regression performance
- trained feed forward networks do <u>not</u> perform significantly worse than the human listeners

Discussion and Conclusions

Setting of the perception experiment

- humans are able to perceive intonation similarities wrt judgement consistency
- worse performance of non-German natives: perhaps different prominence perception of center syllable
- not addressed yet:
 - longer segments than one target syllable
 - possible interference between perceptual similarity of two contours and their functional equivalence (Kohler, 1987)

Physical representation of perceived similarity

• low correlations for metrics in isolation and in combination

• possible reasons:

- not all physical influence factors have been found yet
- factors work together in a more sophisticated manner than examined here
- the appropriateness of metrics is not adequately expressed in terms of correlation alone (see below)
- **further extensions:** e.g. weighting the contour distances by intensity (Clark&Dusterhoff, 1999)
- proposed method to determine the relative weight of influence factors by grouping them to PCs and by comparing the PC weights in a linear regression model

Model evaluation

- possible to develop acceptable feed forward network models to predict intonation distance
- performance not significantly worse than human performance vs. low correlation between model outputs and human perception data →
 suggesting that a model's performance is not adequately expressed in terms of correlation alone

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