Variation, variability and category overlap in intonation

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A major issue in intonation research is modelling the variability of F0 contours while capturing significant generalizations that guide phonological abstraction. Some models ignore variability altogether by dealing with idealized contours [1]; others [2] focus on capturing variability, but at the expense of generalization [3]. The autosegmental-metrical model of intonational phonology (AM, [4]) captures phonological generalizations but has difficulty dealing with variability, as its diagnostics rely on phonetic invariance: tonal targets are the reflexes of underlying tones if they show invariant alignment and scaling. This criterion is at odds with the extent of variability found in natural speech, e.g. [5], and thus requires radical rethinking.

Here we investigate variability in a Greek corpus including 844 tokens of three pitch accents (H*, L+H* and H*+L) all of which appear in utterance-final, nuclear position. The data were collected from Greek speakers (10F, 3M) reading four repetitions of dialogues designed to elicit the three accents on test words with varied stress; see (1). For each test word, the three-syllable interval ending at the offset of the stressed syllable, underlined in (1), was marked and its F0 extracted using STRAIGHT [6]. The F0 curves of this interval underwent Functional Principal Component Analysis (PCA). PCA returns the most dominant modes of variation in functional form, called Functional Principal Components (PCs). Every input curve then receives a coefficient for identified PCs, representing the contribution of each PC to that curve's shape. PCA, and the coefficients for PC1 and PC2 (henceforth *scores*) were statistically analysed together with duration, using linear mixed effects models in R [7, 8] with accent type, stress position, and duration as fixed factors, and speaker as random intercept.

PC1 and PC2 (Fig.1) captured 87.7% of the variance in the corpus (Fig.1), with PC1 reflecting differences primarily in peak height, and PC2 reflecting a combination of contour *shape* and peak alignment (position of the peak in the three-syllable window). Differences in PC1 and PC2 were sufficient to distinguish each accent from the other two (see Fig. 2a), despite the observed overlap between PC scores (Fig. 2b, 2c). Crucially, both PCs were needed to distinguish the accents: PC1 scores were significantly higher for L+H* and H*+L as compared to H*, while PC2 scores were significantly higher only for L+H* as compared to H*. Stress position affected PC1 and PC2 but with H* being less affected than H*+L and L+H*. PC scores also interacted with duration: PC1 decreased with increased duration for both H* and L+H*, while this effect was only observed with respect to L+H* in relation to PC2 (see Fig. 3).

These results showcase the usefulness of data-driven parametrization of F0 curves using PCA, and have consequences for established practices in the study of intonation, especially the invariance criterion. First, they show that variability is widespread but its extent is accentspecific (e.g. H* is less variable than L+H* and H*+L). Second, the results indicate that tonal alignment should not be prioritized over scaling, and that the two are not independent of each other; e.g. PC1 reflects primarily scaling but also differences in peak alignment. Further, accentual contrasts are shown to rely on a number of phonetic dimensions (scaling, peak alignment, segmental duration, curve shape), some of which are more important for some accents than others (e.g. curve shape for L+H*). Finally, some parameters are in trading relations, such as duration and scaling (for PC1), and duration and shape (for L+H* with respect to PC2). Overall, the results suggest that the established research focus on localized F0 targets and invariance as criteria for the phonological status of tonal events risks positing categories that are too fine-grained and capture phonetic variability rather than essential contrasts. Instead the results argue in favour of treating tonal events similarly to segments, i.e. as being expressed by a number of phonetic parameters that show variability and are in trading relationships with each other. A new model based on these principles will be presented and discussed.

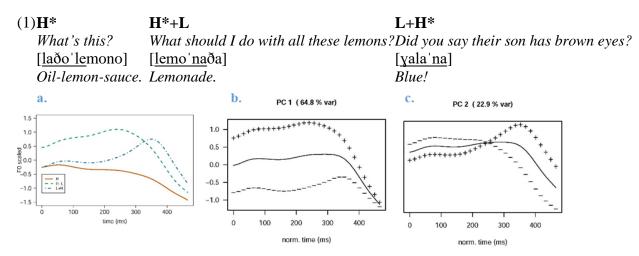


Figure 1. Average F0 contours of pooled data (a); PC1 (b) and PC2 (c) curves modelling the data in (a) [solid black line = mean curve; + = higher PC scores; - = lower PC scores].

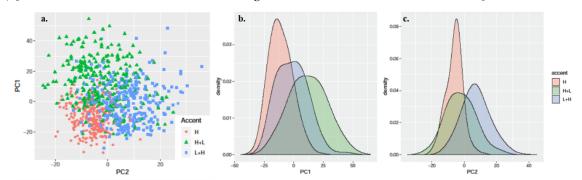


Figure 2. Scatterplot of PC1 * PC2 by accent (a); density plots for PC1 (b) and PC2 (c) by accent.

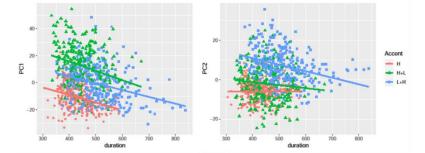


Figure 3. Scatterplots of duration by PC1 (left) and PC2 (right) separately for each accent type.

- [1] 't Hart, J., Collier, R., Cohen, A. 1990. A Perceptual Study of Intonation. Cambridge: CUP.
- [2] Xu, Y. 2005. Speech melody as articulatorily implemented communicative functions. *Speech Communication* 46(3-4): 220-251.
- [3] Arvaniti, A., Ladd, D. R. 2009. Greek wh-questions and the phonology of intonation. *Phonology* 26: 46-63.
- [4]Ladd, D. R. 2008. Intonational Phonology. Cambridge: CUP.
- [5] Arvaniti, A. 2016. Analytical decisions in intonation research and the role of representations: lessons from Romani. *Laboratory Phonology* 7(1): 6, pp. 1–43.
- [6] Kawahara, H., et al. 2005. Nearly defect-free F0 trajectory extraction for expressive speech modifications based on STRAIGHT. *Proceedings of Interspeech 2005*.
- [7]Gubian, M., Torreira, F., Boves, L. 2015. Using functional data analysis for investigating multidimensional dynamic phonetic contrasts. *Journal of Phonetics* 49: 16-40.
- [8] Douglas B., Maechler, M., Bolker, B., & Walker, S. 2015. Fitting linear mixed-effects models using lme4. *Journal of Statistical Software* 67(1): 1-48.
- [9]R Core Team. 2017. R: A Language and Environment for Statistical Computing. https://www.R-project.org/.