L1 Prosodic transfer and priming effects: A quantitative study on semi-
spontaneous dialogues

Giuseppina Turco 1, Michele Gubian 2

1 Max Planck Institute for Psycholinguistics, Nijmegen, The Netherlands
2 Centre for Language & Speech Technology, Radboud University, Nijmegen, The Netherlands

giusy.turco@mpi.nl, m.gubian@let.ru.nl

Abstract

This paper represents a pilot investigation of accentuation patterns produced by advanced Dutch speakers of Italian as a second language (L2). Contrastive accent patterns within phrases were elicited in a semi-spontaneous dialogue entertained with a confederate native speaker of Italian. The aim of the analysis was to compare learners’ contrastive accentual configurations induced by the confederate speaker’s prime against those produced by Italian and Dutch natives in the same testing conditions. F0 and speech rate data were analysed by applying powerful data-driven techniques available in the Functional Data Analysis statistical framework. Results reveal different accentual configurations in L1 and L2 Italian in response to the confederate’s prime. We conclude that learner’s accentual patterns mirror those ones produced by their L1 control group (prosodic-transfer hypothesis), although the hypothesis of a transient priming effect on learners’ choice of contrastive patterns cannot be completely ruled out. 

Index Terms: prosodic transfer, (semi)spontaneous speech, priming, Function Data Analysis, Principal Component Analysis

1. Introduction


In the psycholinguistics literature, studies on associative priming [4] support the hypothesis that contrastive intonation contours induce semantic processing that can lead to priming effects. For instance, a study on L2 priming [5] showed that in perception, L2 listeners processing of intonational meaning depends on the prosodic system of their L1. Another study [6] assessing priming effects in L1 production suggests that even if prosodic representations can be primed, this effect is only short-lived.

This paper investigates whether L1 prosodic-transfer effects and short-lived priming effects coexist in accentuation patterns produced by L2 advanced Dutch speakers of Italian. A confederate speaker was involved in a dialogue-game and had the role of eliciting contrastive phrases from participants. We chose to test learners with Dutch-Italian as L1-L2 language pairs because previous experimental studies [7] support the hypothesis that Germanic and Romance languages differ in how prosody is exploited for marking information status [8]. [7] found that Dutch native speakers typically tend to accent new words and deaccent given (’repeated’) words within syntactic constituents. Such a prosodic-pragmatic relation, by contrast, was not found in (Tuscany) Italian (but for a different account on Italian deaccentuation see [9]).

Our choice of Italian and Dutch is thus aimed at finding measurable correlates of L1 prosodic transfer in systematic differences in F0 contour shapes realised by the different speaker groups. F0 contours, together with relative speech rate information, were processed using Functional Principal Component Analysis (FPCA), a modern statistical tool available within the framework of Functional Data Analysis (FDA) [17]. FPCA allowed to assess and visualize significative differences in the shape of F0 contours belonging to the different speaker groups. The results of this analysis formed the basis of the discussion that is reported in Sec.4. FDA is a set of techniques relatively new to the speech research community. The interested reader can refer to lands.let.ru.nl/FDA.

2. Experiment

2.1. Experimental setting

The experiment where the material of the present analysis is elicited from is a picture-difference task and this was designed for other research purposes than the ones tested in this paper (for details, see [10]). This task was based on a picture comparison in dialogue form between a confederate speaker and the participant, thus allowing for the elicitation of a semi-spontaneous production. The task was to spot differences across pictures: the confederate had to contrast her picture in relation to a reference baseline picture, always by holding the first turn in each trial; then, the participant took the turn and had to contrast his/her own picture in relation to the confederate’s one.

2.2. Material and Participants

The material consisted of 32 semi-spontaneous utterances per speaker. All utterances always started with the same phrases (for Italian: “Nella mia immagine”; for Dutch: “Op mijn plaatje”: “In my picture”) consisting of a function word (“mia”-“mijn”) followed by a content word (“immagine”-“plaatje”). These phrases were always produced in a contrastive setting where confederate and participants had the role of contrasting each other’s picture. Within such a scenario, we assumed that the contrast (and therefore the new information) would be realized on “my” rather than “picture”, even if both words were repeated across the prime and the target phrases.

We collected data from 8 Dutch natives (m=2, age av.=21.2, sd=1.2) and 8 Italian natives (m=4, age av.=23.3, sd=2.3) and from 9 Dutch learners of L2 Italian (m=2, age av.=43.8, sd=9.7). For the collection of the L1 and the L2 Italian datasets, an Italian confederate native speaker was
involved in the task, for the collection of the L1 Dutch dataset, a Dutch native speaker. Confederates were not directly instructed on which intonation contour to use but only told to produce very similar intonational realizations throughout all the sessions and for each speaker. The speech production of the Dutch confederate was not used for the present analysis given that this was not relevant for the priming effect issue.

The L1 Dutch dataset (N, hereafter) consisted of 231 prepositional phrases; the L1 Italian (I) dataset of 246; the L2 Italian dataset (L) of 218. The Italian confederate dataset (C) consisted of 120 prepositional phrases. Phrases containing ellipsis or hesitations were discarded from the analysis. A post-experiment analysis of the confederate’s sentences revealed that she realized the contrast on the phrases by constantly using a pre-nuclear accent on “mia” and a falling nuclear accent on “immagine” (H* H+L* L% according to ToBt [11]). Finally, learners’ language proficiency was classified as intermediate according to a writing assessment test.

3. Data Analysis

3.1. Forced Alignment and F0 extraction

The prosodic analysis of this work is based on two types of input data. The first data type consists of sampled F0 contours, the second one consists of sequences of phone boundaries. The latter has two purposes: a) aligning F0 contours according to the segmental material, b) inferring information about local speech rate.

F0 contours were computed using the F0 tracker available in the Praat toolkit [12]. A default range of 70-350 Hz for males and 100-500 Hz for females was used. These ranges were adjusted for specific speakers in order to minimize obvious errors such as octave jumps. Values of F0 were then transformed into semitones and the mean value of each contour was subtracted out, in order to minimize gender-related differences.

Boundaries between adjacent phones were computed using ASR-based forced alignment. The Italian material consists of repetitions of the phrase “nella mia immagine”. Such material was assigned the broad phonetic transcription /nela mia imadZine/ (SAMPA notation [13]), a slight simplification of the canonical form. This aligner is based on the SPRAAK ASR toolkit [14] and the models are trained on eight hours of Italian speech [15]. Similarly, the Dutch material consists of repetitions of “op mijn plaatje”, which was transcribed as /op mEin pla:tj@/. Also the Dutch material was aligned using SPRAAK, the acoustic models are trained on the read speech part of the Corpus of Spoken Dutch (CGN[16]).

3.2. Principal Component Analysis of contours: overview

Principal Component Analysis (PCA) is a classic dimensionality reduction technique. In this work, we applied an extension of PCA that allows data elements to be contours. This is called Functional PCA (FPCA) and it is one of the techniques available within the framework of Functional Data Analysis [17], a set of modern statistical tools for the analysis of data in the form of functions, where “function” refers to the mathematical representation of a curve (e.g. a polynomial).

Given a dataset of contours, F0 in our case, FPCA offers a compact description of the different contour shapes that can be found in the dataset. Every input curve is represented by a combination of a small number of principal curves, which are the same for all input curves, but are combined in different proportions. Formally, each input curve \( f(t) \) \( (t \text{ refers to time}) \) is represented, or better, approximated by a linear combination of fixed functions. One is the mean \( m(t) \), i.e. a curve whose value at any instant \( t \) is the arithmetic mean of all input curves at \( t \). The others are the so-called Principal Components (PCs), which are found by the FPCA algorithm solely on the basis of the input dataset and are ordered by explanatory power (in terms of percentage of explained variance). If we limit ourselves to the first two PCs, then each curve \( f(t) \) is represented by:

\[
f(t) \approx m(t) + s_1 \cdot PC_1(t) + s_2 \cdot PC_2(t)
\] (1)

where \( s_1 \) and \( s_2 \) are called PC scores and are real numbers that determine the proportion with which PC curves have to be combined in order to reproduce the shape of \( f(t) \) as faithfully as possible. Fig.1 illustrates the mechanism for PC1 only, where we see how adding \( s_1 \cdot PC_1(t) \) to \( m(t) \) produces a better approximation of \( f(t) \) than using only \( m(t) \).

The form of FPCA output offers the possibility to bind a qualitative description of curve shapes to a numerical counterpart. Since each original input curve is associated to a set of numerical scores, classic statistical tools can be applied to those scores to produce inferences. At the same time, scores have a precise relation to curve shapes by virtue of eq.(1), thus any statement on PC scores can be translated into a statement on contour shapes.

In this work, FPCA has been applied in two conceptually distinct stages. First, all F0 contours were processed by FPCA to produce a mathematical description of the whole dataset. In this stage, the membership information of each F0 contour to its speaker group \( (I, N, L \text{ or } C) \) was not used. In the second stage, the distribution of PC score values \( (s_1, s_2) \) obtained in the first stage was related back to speaker group membership. Four distinct clusters were clearly identifiable in the \( (s_1, s_2) \) space, showing that the four groups have distinctive F0 contour shape traits. The centroids of those clusters where used to construct prototype curves by virtue of eq.(1). These prototypes (mean curves) became the basis for a qualitative description in terms of pitch accent characterization reported in Sec.4.

3.3. Landmark registration and speech rate

The first step towards the application of FPCA to a set of sampled F0 contours is to represent each contour by a continuous function \( f(t) \), which is the required input form for FPCA. Every function has to approximate the shape suggested by its corresponding F0 sample sequence, but does not have to become too much rough or wiggly, because we do not want to include unnecessary detail due to errors of the F0 tracker or to microprosody. This is achieved by applying standard smoothing techniques (B-splines-based smoothing with roughness penalty [17]).

It is customary to analyse F0 contours by referring them to the underlying segmental material, as opposed to absolute time. However, each F0 contour has a different duration, and also each word or syllable is in general pronounced at a different rate across repetitions. To make FPCA work on F0
contours referred to the segmental material, an operation called *landmark registration* is applied [17]. This warps the time axis in such a way that it synchronises the position of a number of segmental boundaries selected by the user. In this way, all F0 contours appear to cross a certain boundary exactly at the same time, thus making the results of FPCA meaningful for a prosodic analysis.

To preserve the relative duration of corresponding segments, the second author proposed a way to recover and integrate this information into FPCA by attaching a corresponding relative speech rate contour to each F0 contour [18].

Since our material includes two different phrases, we had to decide on a common set of comparable segmental boundaries. We placed three internal boundaries as follows: /a | mia | ima | dZine/ for the Italian material (thus cutting the first unstressed syllable /ne/), and /op | mein | plac | jf@/ for the Dutch material (underline denotes lexical stress).

### 3.4. Results

The application of FPCA to the entire dataset of F0 contours produced the PC scores distribution plotted in Fig.2. Each point represents the values of s1 and s2 for each F0 contour as in eq.(1), and it is labeled according to the speaker group it belongs to. We note four distinct clusters. This means that the shape characteristics described by the first two PCs, together explaining 54.2% of the variance, strongly correlate with speaker group membership. Since FPCA does not make use of the group membership information, i.e. the labels were added after FPCA was carried out on the entire dataset, the appearance of those distinct group-related clusters in the (s1, s2) space provides evidence that the four speaker groups differ from one another in the way they produce their F0 contours.

To verify this, an ANOVA followed by a Tukey HSD test was performed on each of the two complete sets of PC scores separately, with groups I, N, L and C. Results revealed that the means of each group (marked as triangles in Fig.2) are statistically different from each other (p<.0001) in at least one of the two PC scores, which are not correlated by construction. This result allowed us to plot four prototypical curves and safely discuss their shape traits, since these traits represent significant differences among F0 contour realisations for each speaker group. Fig.3 shows the four F0 prototypical curves obtained by applying eq.(1) to the four cluster centroids (i.e. substituting s1 and s2 with the centroids coordinates).

The same operation was done for the associated relative speech rate curves in Fig.4. The latter plot reports relative speech rates, i.e. the value 1.0 means average rate, 2.0 means twice as fast as average, or duration two times shorter. Average rates are computed from the durations of matching segments in the alignment described in Sec.3.3. The prototypical curves in Fig.3 and 4 are used in the discussion that follows.

### 4. Discussion

Before discussing our results in relation to the L data, it is worth talking about the different accentual configurations produced across the dialogues between groups I and C. In I, the peak culminates in the stressed syllable of "*mima*" (as indicated in Fig.3, 3rd interval), whereas C realizes the peak on "*ma*" (Fig.3, 2nd interval), followed by a very steep fall on the syllable "*mma*" (Fig.3, 3rd interval). This difference is a clear indication that I and C are using two different pitch accents in signaling the contrast to each other’s picture. We can speculate that sequential effects of turn-taking in the dialogue might have caused a different accentual configuration choice across turns. Recall that C always speaks first.

![Figure 1: An example of an application of eq.1 limited to PC1 only. One F0 curve f(t) (’o’ curve) selected from the data set is approximated (‘+’ curve) by summing the mean curve m(t) (’m’ curve) and the first principal component PC1(t) (’1’ curve), the latter multiplied by the score s1 associated with f(t), in this case, s1=1.78.](image1)

![Figure 2: Scatterplot of the values of the first two PC scores s1, s2 as in eq.(1). Speaker group membership is indicated with I(Italian), N(Dutch), L(learners) C(Confederate) labels are marked with a triangle.](image2)
configuration as the N (i.e. a peak on “mijn”) and that the shallow slope of L’s fall is very similar to that one realized by the natives. The reader should bear in mind that the F0 curve of N is actually steeper than how it is represented in Fig.3, by virtue of the corresponding increase of speech rate reported in the previous one in the dialogue; ii) learners’ prototypical curves had features similar to the confederate’s and to the L1 Dutch. However, we could not attribute these similarities to either a case of prosodic-transfer or to a priming effect. Future experiments could be designed to explore L2 learners ability of accommodating their accentual configurations in the complex chain of relations entailed by a dialogue.

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7. References


5. Conclusions

In this study, accent-patterns in L2 Italian produced by Dutch learners in semi-spontaneous dialogues were compared to control groups and explored by using Functional Data Analysis. Our findings are in line with previous studies [7, 8] on cross-linguistic differences in prominence patterns. The study reveals that i) learners differed from L1 natives in how they realized their accent configuration in relation to a previous one in the dialogue; ii) learners’ prototypical curves had features similar to the confederate’s and to the L1 Dutch. However, we could not attribute these similarities to either a case of prosodic-transfer or to a priming effect. Future experiments could be designed to explore L2 learners ability of accommodating their accentual configurations in the complex chain of relations entailed by a dialogue.