Phonetic Entrainment in Cooperative Dialogues: A Case of Russian

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Abstract

It has been shown for a number of languages that speakers accommodate to each other in conversation. Such accommodation, or entrainment, reveals itself in many modalities including speech: interlocutors are found to entrain in intensity, fundamental frequency, tempo and other acoustic features. This paper presents data on speech entrainment in Russian using the standard measures for speech entrainment: proximity, convergence and synchrony. The research uses 49 dialogues from the SibLing speech corpus where speakers played a card-matching game. The list of acoustic features includes various measures of pitch, energy, spectral slope, HNR, jitter, and shimmer. The results for Russian are compared with those published previously for other languages.

Index Terms: phonetics, dialogue, speech entrainment, card-matching game, Russian

1. Introduction

In recent years a lot has been published on speech entrainment—the phenomenon of speakers’ adaptation to each other in conversation. The published results encompass a significant number of languages. Among them are Chinese [1], English [2, 3, 4, 5, 6, French [7], German [8, 9], Italian [10], Japanese [11, 12], Polish [13], Portuguese [14], Slovak [15], Spanish [16], Swedish [17] and others. For the scientific community it is crucial to collect data for other languages as well: the more languages are on this list, the more proof we get of the universal nature of speech accommodation, and, on the other hand, the more language-specific traits we describe.

Most of the research on speech entrainment is based on dialogues where interlocutors are solving a common task, as the cooperative nature of such conversations provides ground for hypothesizing that we may expect accommodation. Among the most frequently used tasks are searching for similar objects on the pictures (card-matching game) or arranging pictures in a specific order [18, 15, 1, 16, 19] and describing a route drawn on a map (map task) [3, 20, 5, 21, 14, 22].

So far, Russian speech material has never been used for research in the field of speech entrainment. This is why we recorded a new corpus of Russian dialogue speech SibLing which is now at the final stages of development [23]. The corpus contains recordings of collaborative dialogues where interlocutors play a card-matching game and a map task. The basic set of speakers consists of 10 pairs of same-gender siblings (including 4 pairs of identical twins) aged 23–40. Each of the siblings participated in five dialogue sessions: with the other sibling, with his/her close friend of the same gender and similar age, with a stranger of the same gender and similar age, with a stranger of similar age and different gender, with a stranger of a higher job position, same gender and greater age.

In the card-matching game the interlocutors were searching for similarities in two decks of ten cards. The speakers took turns to describe their picture, but in most cases the role differences (information giver vs. information follower) almost disappeared after the first switch. The map task was a classical task in which the interlocutors explained to each other routes drawn on schematic maps.

Our analysis of this data showed that in map task most speakers’ acoustic features differ significantly across their roles in the dialogue (information giver vs. information follower), but card games are more role-neutral. This is why at this stage we limited our analysis by card games only, leaving the map task recordings for our future research.

The total amount of the analyzed material is over 10 hours. The dialogues were recorded in a soundproof studio. The interlocutors were separated by a non-transparent screen to prevent them from seeing each other.

2. Method

2.1. Material

The results presented in this paper are based on 49 dialogues from the newly created corpus of Russian dialogue speech SibLing which is now at the final stages of development [23]. The corpus contains recordings of collaborative dialogues where interlocutors play a card-matching game and a map task. The basic set of speakers consists of 10 pairs of same-gender siblings (including 4 pairs of identical twins) aged 23–40. Each of the siblings participated in five dialogue sessions: with the other sibling, with his/her close friend of the same gender and similar age, with a stranger of the same gender and similar age, with a stranger of similar age and different gender, with a stranger of a higher job position, same gender and greater age.

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2.2. Acoustic features

A set of 16 acoustic features was used to explore speech entrainment, including those related to pitch, energy, spectral slope and voice quality. The features are listed in Table 1.

This set of acoustic features was calculated for each IPU (inter-pausal unit). F0, jitter, and shimmer were calculated over...
the whole IPU. Energy, HNR and spectral slope were extracted frame-wise using non-overlapping 10 ms frames. The acoustic analysis was performed by means of our own tools implemented in Python 3 using librosa library to extract spectral features [25].

$F_0$ values were extracted using the REAPER algorithm [26]. At the next step we eliminated microprosody and added new $F_0$ values for the voiceless parts of the signal using linear interpolation. Then the contour was smoothed using Savitzky-Golay filtering with a third order polynomial in 5-sample windows [27]. The smoothed $F_0$ values were converted into semitones with the reference frequency of 100 Hz.

Energy was calculated as the arithmetic mean of squared amplitude values and was converted into dB scale.

Harmonics-to-Noise ratio (HNR) was calculated as defined in [28] as the log-ratio of the relative power of the periodic component of the signal and the relative power of the noise component. The periodic component was calculated using the autocorrelation function (AC) at the lag corresponding to the $F_0$ period, while the noise component was calculated as the difference between the $0^{th}$ AC coefficient and the periodic component estimate.

Spectral slope was extracted by the procedure described in [29] as the ratio of the strongest spectral energy peak in the 0–2 kHz region to the strongest spectral energy peak in the 2–5 kHz region. The spectrum was calculated by means of FFT using Hann window.

Jitter and shimmer values were calculated using extracted $F_0$ periods by the procedure described in [30].

Feature values for turns were calculated as arithmetic means across all IPUs within the turn.

### 2.3. Measuring speech entrainment

In this research we calculated three common metrics of phonetic entrainment: proximity, convergence and synchrony (see, e.g., [24]). T-tests and Pearson’s correlation were calculated by means of Python’s SciPy library [31].

For the turn-level (local) proximity the difference between two speakers’ adjacent IPUs was compared with the averaged absolute values of the differences between feature values in the first IPU of the given speaker and the values of the given feature in the last IPUs of 50 % of the other speaker’s turns chosen randomly. The random choice of turns to compare with was motivated by [24]. However, our experiments showed that such proximity estimate varied significantly from one round of calculations to the other. Examples of such inconsistency are given in Table 2, where we present proximity values calculated thrice.

As a result, we explored two modified versions of this method. First, we tried to use not 50 % of the interlocutor’s turns but all of them (except for the current turn). Second, we ran the original method three times, and as significant we considered only those dialogues where all three rounds showed consistent proximity. The difference between all the measures are presented in Table 4.

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<tr>
<th>Features</th>
<th>Measures</th>
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<tr>
<td>energy</td>
<td>mean, max, median, standard deviation</td>
</tr>
<tr>
<td>harmonics-to-noise ratio (HNR)</td>
<td>mean, max</td>
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<tr>
<td>spectral slope</td>
<td>mean, max</td>
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<tr>
<td>shimmer</td>
<td>mean</td>
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</table>

### Table 1: A list of acoustic features used to explore phonetic entrainment.

### Table 2: Three rounds of proximity calculations with averages based on a random set of turns (for 7 dialogues of 49). Empty cell: no significant proximity in all rounds; ‘+’: significant positive proximity; ‘-’: significant negative proximity; ‘.’: no significant proximity (e.g. ‘.’ for max energy in dialogue d11 should read as “negative proximity was found in round 1 and no proximity in rounds 2 and 3”. Significance threshold is 0.05.

<table>
<thead>
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<th>D13</th>
<th>D14</th>
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<th>D16</th>
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<td>$F_0$ max</td>
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There are several ways to measure phonetic convergence. Probably the easiest way is to divide the recording into two halves and compare the average values for a feature between these parts [5]. Another similar approach is to divide the recording into three parts and compare the 1st and the 3rd ones [32]. Then, data across all the dialogues is summarized, and for each feature, convergence is estimated using a paired t-test. These methods estimate global (session-level) convergence.

A fundamentally different approach which does not rely on averages is to estimate local (turn-level) convergence as in [24]; at each turn exchange we measure the between-speaker difference in feature values in the adjacent IPUs (i.e., the last IPU of speaker A’s turn and the first IPU of speaker B’s turn), and then calculate Pearson’s correlation between these values and time. If the correlation coefficient is negative, the between-speaker difference for the feature diminishes with time, which means convergence; positive correlation means divergence; no correlation means either maintenance or asynchrony.

We also tried an alternative way of calculating convergence, comparing adjacent turns instead of IPUs. The comparison is presented in Table 4. Overly short turns were filtered out in order to get rid of backchannels, which are known to have significantly different prosodic features, mostly—duration. Duration threshold was taken as the mean turn duration minus standard deviation calculated across the speaker’s data in the dialogue.

**Synchrony** was calculated as suggested in [24], as Pearson’s correlation between adjacent IPUs in the course of the dialogue. If the correlation coefficient is positive, the speakers “mimic” each other’s speech features, which means positive synchrony; negative correlation means negative synchrony (asynchrony).

### 3. Results and discussion

The detailed information about turn-level proximity, convergence and synchrony is presented in Table 3. The detailed in-
formation includes results obtained for all the features in all the processed dialogues. One can see that the entrainment strategies differ much in the analyzed material. E.g. maximum energy in dialogue d02 shows positive convergence and no proximity or synchrony (‘. . +’). There are cases when different measures show opposite tendencies, e.g. jitter in dialogue d06 shows negative convergence and positive synchrony (‘. . - +’). The summary over all dialogues is given in Table 4.

3.1. Proximity

As mentioned above, the original method for estimating local (turn-level) proximity showed inconsistent results due to random choice of the set of interlocutor’s turns to compare with. Table 2 presents proximity data for 10 features calculated three times on a set of 7 dialogues. One can see that the values are equal in all rounds only in 44 cells (of 70): 33 cases of ‘no significant proximity’ (empty cells). 10 cases of consistent ‘negative proximity’ (‘. . - ’) and 1 case of ‘positive proximity’ (+ + +’). The other cases are examples of changes in proximity decisions. There are cases when one round showed positive proximity and another one showed negative proximity (see, e.g., results for HNR mean in dialogue d14). Because of this, we only counted the cells with either ‘+ + +’ or ‘. . - ’. These results are presented in Table 4, column “random 50 % of IPUs”. However, one may still argue about how to analyse cells with two similar significant values and one non-significant, such as ‘. . - ’, as well as how many rounds should be run in order to get consistent results.

The results for the alternative measurement method, when the set of interlocutor’s turns is not random, are presented in Table 4. We chose this approach as the main method to calculate proximity, and its results for all the dialogues and all the features are presented in Table 3.

Looking at the data presented in the summary (see Table 4) one may see that the two measurement methods for proximity are not much contradictory, as significance tends to appear for roughly the same features. In both cases we conclude that negative proximity prevails and can manifest itself in all acoustic features.

In terms of proximity, more often speakers entrain in F0 features. A similar result was obtained for Mandarin Chinese in [24], while Slovak and English do not show such tendency.

3.2. Convergence

Convergence enables us to understand whether two speakers become closer to each other in the course of conversation—in terms of the given acoustic feature. The experiments on global (session-level) convergence showed different results when dialogues were split into two parts and when dialogues were split into three parts. We found no convergence for any of the features in the former case. In the latter case convergence was found for spectral slope maximum only (p < 0.05, t = 2.242).

As mentioned above, local (turn-level) convergence was measured in two ways: with feature values calculated across the IPU (see Table 3 and Table 4, column “IPU”) and across the whole turn (see Table 4, column “turn”). For both measurement methods, we observe prevalence of negative convergence, but cases of positive convergence are also found. Among the languages discussed in [24], only Slovak shows much negative convergence.

In terms of the acoustic features, there is more frequent negative convergence in features related to energy. This means that in terms of loudness speakers tend to choose the strategy of divergence, while standard deviation of energy shows more cases of positive convergence.

In general, the two measurement methods show similar ten-
cases mostly for energy only. Fests itself mostly in features related to energy and voice quality and syntactic features, gestures and facial movements etc. Trainment can manifest itself many other features—such as lexical and syntactic features, gestures and facial movements etc. Trainment strategies, including no entrainment—at least in some dialogues. Indeed, speakers show different entrainment within the dialogue (globally) does not occur in most cases. However, in certain dialogues we found evidence for synchrony (local “copying” of the acoustic features of the interlocutor, e.g., speaking louder after the interlocutor, then speaking quieter as he/she starts to speak quieter); this is mostly manifested in features related to loudness, more rarely—to voice quality. Synchrony enables us to see whether there are local synchrony (local “copying” of the acoustic features of the interlocutor; e.g., speaking louder after the interlocutor, then speaking quieter as he/she starts to speak quieter); this is mostly manifested in features related to loudness, more rarely—to voice quality. 3.3. Synchrony

Synchrony enables us to see whether there are local synchronous changes in acoustic features in the interlocutors’ speech. In our material positive synchrony prevails and manifests itself mostly in features related to energy and voice quality (see Table 4). Among the languages discussed in [24], positive synchrony is observed for English and Slovak, but in those cases mostly for energy only.

4. Conclusions

In many dialogues we found phonetic manifestations of speech entrainment. Statistical analysis has proved that the way a speaker begins his/her turn indeed depends on the way the interlocutor ended his/her turn; this can be seen in various speech features—related to loudness, melody, voice quality. Entrainment within the dialogue (globally) does not occur in most cases. However, in certain dialogues we found evidence for synchrony (local “copying” of the acoustic features of the interlocutor, e.g., speaking louder after the interlocutor, then speaking quieter as he/she starts to speak quieter); this is mostly manifested in features related to loudness, more rarely—to voice quality.

Still, our data confirms the thesis of high variability across speakers and dialogues. Indeed, speakers show different entrainment strategies, including no entrainment—at least in terms of these features and these metrics. It is known that entrainment can manifest itself many other features—such as lexical and syntactic features, gestures and facial movements etc. The latter, however, we tried to eliminate here by putting a non-transparent screen between the speakers.

There is still much to be done to solve the issues concerning the measurement method. First, averaging within an IPU may add noise to the analysis for short IPUs. But even switching to turns instead of IPUs will not solve the problem, as turns may be short as well. Given that most of the short turns are backchannels, which differ prosodically form other turns, short turns should be completely excluded from this analysis; at the same time, backchannels themselves may manifest speech entrainment—which should be analyzed separately. Second, proximity measurement method can be improved in two ways, as we discussed in this paper: by either running the random-IUU-based analysis several times, or analyzing all of the interlocutor’s turns.

In general, our data confirms the universality of speech entrainment. But when we compare our results to those for English, Slovak, Spanish and Chinese, we find that Russian is significantly as well, with the only cross-language generalization that it resembles Chinese, in terms of synchrony—Standard American English, and in terms of convergence—more ore less, Slovak. But the results are still hugely variable between speakers. The acoustic features that manifest accommodation vary significantly as well, with the only cross-language generalization that the most prominent are energy-related features.

In the recent decades, a lot of research has been done on the social and individual factors influencing speech entrainment (see, e.g. [33]). This is why our next step is to include some of these factors in our analysis—the SibLing corpus that we used here enables to analyse the data with respect to gender, conversational roles, degree of speakers’ familiarity, and social hierarchy.

5. Acknowledgements

This research is supported by the Russian Science Foundation (grant 19-78-10046).

<table>
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6. References


