Neural representations of dialogical history for improving upcoming turn acoustic parameters prediction

Simone Fuscone\(^1\), Benoit Favre\(^2\) and Laurent Prévot\(^1\)

\(^1\) Aix-Marseille Univ, CNRS, LPL, Aix-en-Provence, France
\(^2\) Aix Marseille Univ, Université de Toulon, CNRS, LIS, Marseille, France
\(^3\) Institut Universitaire de France, Paris, France

simone.fuscone@univ-amu.fr benoit.favre@lis-lab.fr laurent.prevot@univ-amu.fr

Abstract

Predicting the acoustic and linguistic parameters of an upcoming conversational turn is important for dialogue systems aiming to include low-level adaptation with the user. It is known that during an interaction speakers could influence each other speech production. However, the precise dynamics of the phenomena is not well-established, especially in the context of natural conversations. We developed a model based on an RNN architecture that predicts speech variables (Energy, F0 range and Speech Rate) of the upcoming turn using a representation vector describing speech information of previous turns. We compare the prediction performances when using a dialogical history (from both participants) vs. monological history (from only upcoming turn’s speaker). We found that the information contained in previous turns produced by both the speaker and his interlocutor reduce the error in predicting current acoustic target variable. In addition the error in prediction decreases as increases the number of previous turns taken into account.

Index Terms: convergence, prediction, acoustic features, prosody

1. Introduction

Throughout the course of a conversation the conversants, the one who has the floor alias the ‘speaker’ and his interlocutor, try to explain the influence that a speaker has on its interlocutor’s production and vice versa. We aim to expand the work that have been done in this direction. Our approach is to build a regression problem that consists in predicting some acoustics parameters of the upcoming turn using information contained in previous turns. Our method to study convergence consists in the estimation of the influence that the speech style of the interlocutor has on the speech style of the speaker in the upcoming turn.

The understanding of convergence mechanisms is crucial in the development of virtual agents for human robot interaction. Developing virtual agents that mirror human behavior could improve the success of communication between humans and virtual agents. Past literature showed that convergence is higher with human peer than a simple virtual agent ([6, 7]) and that a system that converges to the human speaker increases the success in accomplishment of a task ([8]) or that ([9]) speakers tend to ask advice mostly to systems that converge with them.

In this paper we introduce an exploratory methodology to study convergence by evaluating whether using information contained in the previous turns produced by both speaker and interlocutor leads to have better prediction of upcoming turn acoustic parameters than using information of previous turns produced by just the speaker. The paper starts with a review of related works (Section 2) that focused on the influence that conversants play on each other. Then we describe the model, the data and the feature extraction methods in Section 3. Using the Switchboard data set we present the experiments and results we obtained using as target the mean energy, pitch range and speech rate (Section 4). Finally, we discuss possible improvement and extensions of this approach (Section 5).

2. Related work

The target variables we scrutinize in this study - Energy (E), Pitch range (F0) and Speech Rate (SR) - were object of study in previous works. E is the speech variable regularly cited that exhibits convergence effects between speakers in both experimental [10], [11], [12] [13] [14] and natural conversations [15], [16]. Alongside [17, 18] describe convergence in F0 max for successfully interactions while [19] observe convergence both in average and range F0. Besides studies that measure convergence looking at the distance between the conversants some authors, at the best of our knowledge, focused on the influence between the previous productions of speaker and his interlocutor with predictive paradigms. Cohen et al. [20] use a linear mixed model to estimate average SR in a conversation using the average SR of his interlocutor. Similarly, Cohen & Sanker [21] apply this approach to F0. In a more fine-grained approach Schweitzer and colleagues [22, 23] used SR of previous turn values to predict SR of upcoming turn using a linear mixed model. These methods account to get the correlation between the same variable (here, SR) but did not consider the relation that other speech features may have on the variable studied. We expand these studies to question the influence that each conversant has on his partner by looking if the information contained in previous history of the conversation helps to predict the evolution of acoustics features.

3. Methods

3.1. The Model

The regression problem is illustrated in Figure 1. The model takes as input the representation vector of the $N$ ($1 \leq N \leq$
Table 1: Distribution of turns: we report for each N, the percentage of turns produced by S and I. The S > I means that the S produced more turns than I, the opposite for S < I while S = I that S and I produced the same numbers of turns.

<table>
<thead>
<tr>
<th>N</th>
<th>S &gt; I</th>
<th>S &lt; I</th>
<th>S = I</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>32%</td>
<td>68%</td>
<td>-</td>
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<tr>
<td>2</td>
<td>11%</td>
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<td>3</td>
<td>41%</td>
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<tr>
<td>4</td>
<td>19%</td>
<td>30%</td>
<td>51%</td>
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<tr>
<td>5</td>
<td>44%</td>
<td>56%</td>
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<tr>
<td>6</td>
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<td>7</td>
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<td>8</td>
<td>28%</td>
<td>34%</td>
<td>38%</td>
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<td>9</td>
<td>46%</td>
<td>54%</td>
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<tr>
<td>10</td>
<td>31%</td>
<td>36%</td>
<td>33%</td>
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</tbody>
</table>

3.3. Feature extraction

E and F0 are computed from the audio files with openSMILE audio analysis tool [27] while SR is computed using time aligned transcripts. In this section we will describe in details the extraction and computation of the target features and the other features that are taken into account as input variables in the representation vector.

**Energy (E):** The mean value per each turn is computed as the average of values that have been sampled every 50 ms. To handle the distance mouth-microphone, which could vary during a telephone conversation affecting the voice intensity, we introduce a normalization factor consisting of dividing each speaker E value by the average E produced by that speaker in the entire conversation. In addition, to reduce the environmental noises, we computed the average E using the temporal windows where the probability of voicing is above 0.65.

**Pitch range (F0 range):** It is the distance between the max and min of F0 that were sampled every 50 ms, adopting the same filtering procedure applied for E.

**Speech Rate (SR):** We used the approach proposed by Cohen Priva [20] that defines SR for an utterance as the ratio between the actual duration of the utterance and its expected duration (computed by estimating every word duration into the whole corpus, for all speakers). Values above / below 1 correspond respectively to fast / slow speech compare to the average of the corpus.

**Duration (Δ):** It refers to the temporal length of each turn, as provided by the segmentation of the SW corpus.

**Dialog acts (DA) type:** We use as predictors the kind of speech activity that indicates the type of turn. From the NEX Switchboard (SWB-NXT) [28], we developed a DA-tagger to cover the whole data set.

We simplify the tagging task by considering only 3 categories resulting from the merging of the 42 original ones: Statement+Opinion (STA+OPI), Backchannel+Agreement (BAC+AGR) and Other (OTH) which includes all the other DA. This grouping was obtained by first considering only the DA which dominates the distribution. Then we manually inspected many examples of each dialogue act and figured out that, although functionally different, statements and opinions on the hand backchannel and Agreement on the other hand correspond to very similar conversational activities. More precisely, the former have clear main speaker feeling with a lot of semantic content while the latter have a much more listener
nature with various kind of feedback related lexical items.

We used as train, development and test set the SWB-NXT corpus that contains annotated DA for 642 conversations. As the DA don’t match the turn segmentation, we label each turn of the corpus by assigning one of the majority class, among the DA tags that forms the turn. The distribution results to be formed by 52% of STA+OPI, 25% of BAC+AGR and 23% of OTH. The model we used is described in ([29]) and inspired by the model of ([30]). It is a two levels hierarchical Neural Network (with learning rate = 0.001, batch size = 32, max length of each turn = 80, embeddings words dimension = 200). In the first level each turn is treated singularly taking into account the words that form the turn while the second level is used to take into account the whole turn in the context of the conversation. Each level is a bidirectional Long Short Term (LSTM). We used 80% of switchboard data as training set, 10% for development and 10% for the test set. The F1 score of the DA tagger is BAC+AGR = 86%, STA+OPI = 87% and OTH = 55%. The F1 score of the class OTH, as expected, is low compared to the other 2 classes considering that it is formed by heterogeneous DA acts.

4. Experiments and Results

4.1. Training the Model

For each target and each setup (S vs S+I), we applied a random search grid to chose the learning rate of the Adam optimizer and the hidden size of the output of LSTM. We evaluate the performances on a validation set using the L1 smooth Loss (E: lear. rate = 0.0022, size layer = 36; F0 range: lear. rate = 0.0025, size layer = 40, SR: lear. rate = 0.0022, size layer = 36).

4.2. Energy

Feature Selection. Our first aim is to select the variables of speech production described in 3.3 (Energy, Pitch, Speech Rate, Duration, Dialogue Act type) to build the representation vector that will be used as input in our model. As criterion of selection we chose the subset of variables that has the better performance over the turns. Table 2) shows that the vector representation formed by E, Δ and DA is the subset that improves significantly the performances in predicting the mean E of the upcoming turn compared to the other variables, for both the S and S+I setups. The use of the complete representation vector doesn’t lead to a significant improvement of performance. We used a K-fold approach with K = 10 and use a dependent t-test to compare the different subsets applying the recursive features elimination method.

Speaker vs Speaker + Interlocutor. When we include interlocutor’s history, results show that the use of a representation vector formed by the selected features of both speaker and interlocutor brings to a significant ($p < 10^{-8}$) decrease of L1 loss than just using turns produced by the speaker (Figure 3). Secondly, using our model has better performances in predicting the mean energy of the upcoming turn compared to the use of the linear regression (Speaker estimate = 0.318 ± 0.004, Interlocutor Estimate = −0.149 ± 0.003). As expected consequents follow the trend of the more recent turns history (see Table 3).

4.3. Pitch Range

Feature Selection Similarly to the experiment about energy we compare the different subsets of features (See 3.3). Here again, results show that the richer representation improves significantly the performances in predicting the F0 range of the upcoming turn compared to the use of only F0 range of the previous turns (Table 2) but it is not significantly better than the subset formed by just F0 range (the target), DA and Δ. We used a K-fold approach, with K = 10, and use a dependent t-test to compare the subsets of features, per each turn and per each setup (S and S+I).

Speaker vs Speaker + Interlocutor As for energy, using of a representation vector formed by the selected features of both speaker and interlocutor leads to a significant decrease ($p < 0.05$) of L1 loss than just using turns produced by the speaker (see Figure 4 and Table 3). The use of our model improves performances in predicting the F0 range of the upcoming turn compared to the use of the linear regression. The L1 loss is the same in the case of the baseline for both S and S+I as the estimate of the linear regression for interlocutor is close to zero (estimate = −0.024 ± 0.003 while the one of the speaker is 0.409 ± 0.004). Adding more turns to the previous history causes the error decrease both in our model and in the baseline.

Speech Rate For SR we don’t observe any significant difference between the S and S+I setups (Figure 5 and Table 3).
The reason could be that the measure of SR we adopted is sensitive to the length of the words and this effect is amplified for short turns.

### 5. Discussion and Conclusions

In this paper we presented a new method to evaluate convergence, consisting in predicting some acoustic parameters of the upcoming turn in a conversation. The idea is to evaluate if the speech style of a speaker is influenced by the speech style of his interlocutor. We introduced a first simple model to predict the value of energy, F0 range and speech rate in the upcoming turn. For E the decrease is highly significant (p-value < 10^{-8}) while significant for F0 range (p-value < 0.05) for all the N turns we explored. This result is in agreement with past studies that claim energy to be a variable that exhibits strong convergence effects (due to a kind of automatic changed of energy as stated by [31]) while F0 shows a weaker of interlocutor influence. Even thought past literature assessed convergence for SR, in this study we do not have evidence that speaker SR is influenced by his interlocutor. The reason could be that the measure of SR we adopted is sensitive to words length and the computation is very noisy in case of short turns. We plan to use another measure of SR in the future.

The subset of features that we selected per each target variable turned out to be the same. It contains the target, the Δ and DA. This confirms that an important variable that controls the speech production and the reciprocal influence of speaker and interlocutor is the structure of the conversation and the type of DA, as [26] explained the lexical information are important to determine the type of DA. As part of these information is contained in DA, we plan to add lexical information as input to explore the influence that they could have on the prediction task.

In addition we observe that the loss decreases as the number of turns of previous history increases for both F0 and SR. This is in agreement with past literature ([20, 32]) that states speakers mainly tend to converge to their baseline (average value that they have in other conversations). On the other hand the trend of E is different as it depends essentially by the most recent turns than the antecedent history.

Even though our goal is not to build a system that adapts to human interlocutor such results should be of interest either as justification or inspiration for anyone interested in building artificial systems able to adapt to the user speech characteristics. Our future goal is to generalize the approach to other variables as well as to test the approach on bigger data sets (like the Fisher corpus [33]). It allows to refine the tagger of DA (adding more categories and improving the F1 score of the classification) and improve our model, adding an attention layer.

### Table 3: Results for mean E, F0 range and SR in the case of our model (upper) and the Baseline (lower) for N = 1, 5, 10. ** means that p-value < 10^{-8} while * that p-value < 0.05.

<table>
<thead>
<tr>
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<th>S</th>
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<td>0.416 ± 0.006*</td>
<td>0.371 ± 0.011*</td>
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<td>0.341 ± 0.005</td>
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<tr>
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<td>0.357 ± 0.005</td>
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Baseline, Linear Regr.

<table>
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<th>S + I</th>
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<tbody>
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<td>0.416 ± 0.006</td>
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<td>0.401 ± 0.006</td>
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<tr>
<td>5</td>
<td>0.405 ± 0.005</td>
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<td>0.344 ± 0.009</td>
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<td>0.331 ± 0.005</td>
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<tr>
<td>10</td>
<td>0.413 ± 0.006</td>
<td>0.413 ± 0.006</td>
<td>0.335 ± 0.010</td>
<td>0.335 ± 0.010</td>
<td>0.327 ± 0.005</td>
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</tbody>
</table>

**Figure 4:** L1 smooth loss while predicting F0 range of upcoming turn for the S and S+I setups by the use of LSTM model with the richer representation (F0 range, DA and Δ).

**Figure 5:** L1 smooth loss while predicting SR of upcoming turn for the S and S+I setups by the use of LSTM model with the richer representation (SR, DA type and Δ).
6. References


