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Citation for published version:

Link:
Link to publication record in Edinburgh Research Explorer

Document Version:
Peer reviewed version

Published In:
Proceedings of Speech Prosody 2016

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Paragraph-based Prosodic Cues for Speech Synthesis Applications

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Abstract
Speech synthesis has improved in both expressiveness and voice quality in recent years. However, obtaining full expressiveness when dealing with large multi-sentential synthesized discourse is still a challenge, since speech synthesizers do not take into account the prosodic differences that have been observed in discourse units such as paragraphs. The current study validates and extends previous work by analyzing the prosody of paragraph units in a large and diverse corpus of TED Talks using automatically extracted F0, intensity and timing features. In addition, a series of classification experiments was performed in order to identify which features are consistently used to distinguish paragraph breaks. The results show significant differences in prosody related to paragraph position. Moreover, the classification experiments show that boundary features such as pause duration and differences in F0 and intensity levels are the most consistent cues in marking paragraph boundaries. This suggests that these features should be taken into account when generating spoken discourse in order to improve naturalness and expressiveness.

Index Terms: discourse unit, prosodic cue, paragraph boundary, speech synthesis.

1. Introduction
Over the last decade, automatically generated speech has improved significantly, especially in terms of voice quality and expressiveness. However, although a good deal of effort has been spent on building synthetic voices from large multi-paragraph speech databases [1, 2, 3], multi-sentential synthesized speech still suffers from a high degree of unnaturalness. Current Text-To-Speech (TTS) systems generally attempt to improve naturalness and expressiveness by increasing the prosodic variability based on inferred affective states [4, 5]. However, it appears that simply varying sentence prosody, without accounting for paragraph structure, does not necessarily improve naturalness [6]. Instead, it seems that a more discourse structure aware approach is needed to make real improvements in speech synthesis.

Prosodic changes related to discourse in both conversational and read speech have long been observed in phonetic studies. For instance, pitch resets—higher F0 and increased F0 range—are usually found at the beginning of the discourse unit, while pitch declination has been observed across the discourse unit, ending with low F0 [7]. Discourse structure has also been associated with energy and timing features such as pausing, pre-boundary lengthening, and speech rate variations [8, 9]. However, most linguistically oriented studies have been based on small corpora, with relatively small numbers of speakers, and in limited domains. Moreover, few studies have quantified the predictiveness or robustness of these prosodic relationships.

In this paper, we extend previous findings in three aspects. First, we confirm the presence of prosodic cues for paragraph structure in a large, varied corpus of semi-spontaneous speech. To this end, we analyzed a corpus consisting of more than 1300 TED talks and 1100 different speakers. Second, we analyze prosodic patterns in terms of automatically extracted F0, intensity, and timing features of sentences with respect to paragraph position, as well as across paragraph boundaries. Finally, we perform SVM classification experiments to investigate how consistently and robustly specific prosodic cues appear at paragraph boundaries. Taking the results into account could potentially help determine which cues should be implemented in a speech synthesizer in order to improve naturalness and expressiveness of multi-sentential discourses.

The structure of this paper is as follows. Section 2 overviews related work on prosody and discourse structure. Section 3 describes our data set and experimental setup. Results of statistical analyses and classification experiments are described in Sections 4 and 5. We discuss the implications of these results for speech synthesis in Section 6 and conclude in Section 7.

2. The Prosody of Discourse Segments
Prosodic marking of discourse boundaries has been identified in a wide range of instrumental phonetic studies. Early work focused on sentence and paragraph breaks [10, 11], but studies have since investigated prosodic features related to topic changes [12, 13, 14, 15], as well as boundaries related to hierarchical discourse structure [16, 17]. The results of these investigations generally lead to similar conclusions: a speaker’s pitch declines through both intra- and supra-sentential segments, with low boundary tones and laryngealization signalling finality, and mid-level pitch interpreted as continuation or floor holding [11, 12, 18, 19]. Pitch resets are also often observed after discourse boundaries, i.e., increases in pitch level and pitch range at the beginning of the new segment [20, 21, 22]. Similar energy reset patterns have been reported impressionistically [11] or in terms of RMS amplitude [20, 23, 24]. Besides pitch and energy based features, pause length and pre-boundary lengthening have also been identified as boundary indicators [10, 8, 15].

The accumulated results suggest that prosodic boundaries share similar features across discourse levels. So, for example, we expect to see similar prosodic features at sentence internal phrase boundaries and at topic boundaries. Moreover, we expect those prosodic features to be more pronounced for larger units. In line with this, [21] found pause, pitch reset, and boundary tones to be correlated with number of annotators who identified the position as a boundary. Better annotator agreement has also been observed for discourse segmentation when audio is available [21, 23]. In this vein, [25] show that simple rule
based manipulations of F0 topline and baseline and pauses can improve naturalness ratings of synthesized news items.

Although pitch reset and suprasentential pitch declination have been consistently reported as boundary cues, these results have often been based on a mixture of qualitative descriptions of prosodic patterns and signal based measurements, e.g., [11, 18, 24]. This makes the robustness of actual measurable features for signalling boundaries somewhat unclear. Even in more quantitative work, the way prosodic concepts are measured varies from study to study. Such terminological differences can lead to different conclusions about the utility of features. For example, [20] and [21] use F0 maximum as a proxy for pitch range, while other studies use topline/baseline or specified quantile differences [25, 14]. Studies that use the former measure found ‘pitch range’ to have a stronger relationship with discourse structure than those that use the latter.

Using measurable, operational definitions of features is important to understanding how robust prosodic features are for signalling discourse units. Similarly, we’d like to know how well these results generalize to larger sets of speakers and speaking styles. Linguistically oriented studies generally only examine small amounts of data, usually from a restricted domain (e.g., reading aloud of constructed examples or small domain task-oriented dialogues). However, a number of studies have successfully employed prosody and timing features for discourse segmentation using larger data sets, e.g., topic segmentation of broadcast news [26, 27, 28]. Unsurprisingly, features in these studies are usually based around the idea of prosodic reset and differences in pitch ranges, but quantified directly from the speech signal. These segmentation algorithms tend to focus on boundary features, e.g., prosodic statistics of the words immediately adjacent to the boundary [26, 29] rather than declination or other features of the larger discourse unit. For example, [26] find pause duration and F0 range of the word preceding the boundary to be the most discriminative feature for topic boundaries in broadcast news.

Automatic discourse segmentation studies usually aim at detecting at high level discourse units, e.g., changes in news stories or tasks drawn from a pre-defined set [30, 31]. These changes are often signalled by more abrupt, ‘disjunctive’ boundaries [32], which we would expect to occur infrequently while being more prosodically marked. From a speech synthesis point of view, we would like to be able to generate prosody at a more fine-grained level of discourse. Paragraphs are a good point of view, we would like to be able to generate prosody at a more fine-grained level of discourse. Paragraphs are a good

3.2. Feature extraction

3.2.1. Sentence Alignment

TED transcripts come with broad subtitle timings that do not necessarily correspond to sentences in the transcript. To obtain sentence timings, we first obtain precise word timings through Viterbi forced alignment using an automatic speech recognition system. Word timings are then used to automatically obtain sentence boundaries.

3.2.2. Prosodic Features

F0 and intensity contours were extracted using Praat at 10ms intervals with linear interpolation and octave jump removal for F0 [34]. For F0, parameter settings were automatically determined using the method described in [35]. F0 and intensity values were normalized over talks so that zero values represent speaker mean values; intensity measurements (I) were normalized by subtracting the speaker mean for the talk, while F0 values were converted to semitones relative to speaker mean F0 value (Hz), i.e., log scaled to better represent pitch perception.

We calculated aggregate statistics over sentence units: mean, standard deviation, maximum, minimum, median, and slope. We also look at the difference between the first and last words of the sentence (fidiff) and the difference between the 99th and 1st quantile values (range). To capture contextual changes, we measured the difference between the target and the following sentence (sidiff), as well as the difference between the last word of the target sentence and the next sentence (indiff). For these features, we measure the difference from the word or sentence occurring later, so positive difference values indicate a reset to a higher level. In the current work, we only look at differences in means.

1http://www.ted.com

2p.c. TED translation team.
In this section we present the statistics for the sentence and boundary based prosodic features described in Section 3. The differences between the three paragraph positions (first, middle, last) were found to be statistically significant for the individual prosodic features (t-test, \( p < 0.05 \)) except for sd.norm.F0, slope.norm.F0, max.norm.I, slope.norm.I when comparing paragraph middle and last sentences.

Table 1 shows the mean values of sentence-based prosodic features in different paragraph positions. Some clear recurrent patterns can be seen in these sentence-based features. These are exemplified in Figure 1. The first pattern can be characterized by a decrease in feature values through the paragraph. This is shown for mean.norm.F0 in Figure 1a, but was also found in all features representing F0 and intensity level (i.e., mean, maximum, minimum and median) except for median.norm.I. This pattern confirms that declination in prosodic level occurs over paragraph units.

The second pattern (Figure 1b) applies to variation-related features such as range, sd, and the absolute values for fldiff and slope. Here we see reduced values in the middle position, suggesting range compression in the paragraph medial sentences. Note, on first glance, the slope values follow the declination pattern (1a). However, the difference between middle and last sentences was not statistically significant (t-test, \( p > 0.05 \)). Thus, we see a general reduction in the range of variation after the first sentence of a paragraph. Interestingly, however, we do not see relative pitch range compression in paragraph final sentences relative to middle sentences.

Finally, the third pattern, represented by spk.rate in Figure 1c (but also observed for median.norm.I) sees significant increases in the middle position. For speaking rate, this suggests a word lengthening effect in the initial and final positions, which is consistent with pre- and post-boundary lengthening associated with prosodic phrases within sentences [39].

Table 2 shows mean values for boundary-based features obtained looking at sentences in initial and middle positions (no break) versus final position (break). The differences in boundary features in both no break and break classes are all statistically significant (t-test, \( p < 0.05 \)). While a decrease of F0 and intensity is evident when there is no change of paragraph, a clear rise is encountered at the paragraph break in terms of F0, intensity and pause duration. That is, we see clear evidence of prosodic resets over paragraph breaks.
Table 3: SVM classification of individual prosodic features.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Accuracy (%)</th>
<th>AUC</th>
<th>rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>max.norm.F0</td>
<td>51.02</td>
<td>0.510</td>
<td>19</td>
</tr>
<tr>
<td>mean.norm.F0</td>
<td>53.65</td>
<td>0.536</td>
<td>8</td>
</tr>
<tr>
<td>median.norm.F0</td>
<td>54.14</td>
<td>0.541</td>
<td>5</td>
</tr>
<tr>
<td>min.norm.F0</td>
<td>52.75</td>
<td>0.527</td>
<td>11</td>
</tr>
<tr>
<td>range.norm.F0</td>
<td>51.32</td>
<td>0.513</td>
<td>17</td>
</tr>
<tr>
<td>sd.norm.F0</td>
<td>50.63</td>
<td>0.506</td>
<td>21</td>
</tr>
<tr>
<td>slope.norm.F0</td>
<td>53.11</td>
<td>0.531</td>
<td>10</td>
</tr>
<tr>
<td>fldiff.norm.F0</td>
<td>52.13</td>
<td>0.521</td>
<td>15</td>
</tr>
<tr>
<td>max.norm.I</td>
<td>50.97</td>
<td>0.510</td>
<td>20</td>
</tr>
<tr>
<td>mean.norm.I</td>
<td>53.98</td>
<td>0.540</td>
<td>7</td>
</tr>
<tr>
<td>median.norm.I</td>
<td>54.01</td>
<td>0.540</td>
<td>6</td>
</tr>
<tr>
<td>min.norm.I</td>
<td>52.25</td>
<td>0.523</td>
<td>14</td>
</tr>
<tr>
<td>range.norm.I</td>
<td>51.47</td>
<td>0.513</td>
<td>16</td>
</tr>
<tr>
<td>sd.norm.I</td>
<td>51.10</td>
<td>0.511</td>
<td>18</td>
</tr>
<tr>
<td>slope.norm.I</td>
<td>52.68</td>
<td>0.527</td>
<td>12</td>
</tr>
<tr>
<td>fldiff.norm.I</td>
<td>50.45</td>
<td>0.505</td>
<td>22</td>
</tr>
<tr>
<td>spk.rate</td>
<td>52.60</td>
<td>0.526</td>
<td>13</td>
</tr>
</tbody>
</table>

Table 4: SVM classification of selected feature sets.

<table>
<thead>
<tr>
<th>Feature set</th>
<th>Accuracy (%)</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 best</td>
<td>62.87</td>
<td>0.629</td>
</tr>
<tr>
<td>3 best</td>
<td>62.80</td>
<td>0.628</td>
</tr>
<tr>
<td>5 boundary</td>
<td>61.26</td>
<td>0.613</td>
</tr>
<tr>
<td>17 sentence</td>
<td>54.17</td>
<td>0.542</td>
</tr>
<tr>
<td>22 all</td>
<td>56.73</td>
<td>0.567</td>
</tr>
</tbody>
</table>

The current study aimed to determine which prosodic features robustly signal paragraph structure in a large and varied corpus. The statistical analysis highlighted many significant differences over the different paragraph positions, especially in features indicating prosodic level of the target sentences. As in previous studies, these features indicated steady declination in prosodic level over the paragraph. In addition, the variation-related features had lower values in middle positions, suggesting range compression for both pitch and intensity in the middle of the paragraph, with no evidence of pitch range compression specific to the end of paragraphs. Additionally, speaking rate tended to increase mid-paragraph suggesting that first and last sentences are prosodically marked in terms of speaking rate.

Overall, duration appears to be the most robust predictor of paragraph breaks. However, performance is still low, especially compared to previous topic segmentation results. One reason for this may be the subtle relationship between topic and paragraph transitions in TED talks. Another reason is that prosody conveys more than just discourse segment information. From a structural perspective, more analysis of discourse relations, finer grained topic changes, and sentence information structure, are necessary to gain a fuller understanding of the relationship between prosody and discourse.
9. References


