TRAINING INTONATIONAL PHRASING RULES AUTOMATICALLY FOR ENGLISH AND SPANISH TEXT-TO-SPEECH

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Abstract

We describe a procedure for acquiring intonational phrasing rules for text-to-speech synthesis automatically, from annotated text, and some evaluation of this procedure for English and Mexican Spanish. The procedure employs decision trees generated automatically, using Classification and Regression Tree techniques, from text corpora which have been hand-labeled with likely locations of intonational boundaries by native speakers, in conjunction with information available about the text via simple text analysis techniques.

Rules generated by this method have been implemented in the English version of the Bell Laboratories Text-to-Speech System and have been developed for the Mexican Spanish version of that system. These rules currently achieve better than 95% accuracy for English and better than 94% for Spanish. (This paper was presented at the Second ESCA/IEEE Workshop on Speech Synthesis, New Paltz, September, 1994.)

1 Intonational Phrasing

Assigning appropriate phrasing in text-to-speech systems is important both for naturalness and for intelligibility, particularly in longer sentences and longer texts (Silverman et al., 1993). This paper describes the automatic acquisition of methods of assigning these boundaries in real-time unrestricted text-to-speech.

Intuitively, intonational phrases divide utterances into meaningful 'chunks' of information (Bolinger, 1989). Variation in phrasing can change the meaning hearers assign to tokens of a given sentence. For example, the interpretation of a sentence like '*Bill doesn't drink because he's unhappy*' will vary, depending upon whether it is uttered as one phrase or two. Uttered as a single phrase, this sentence is commonly interpreted as conveying that Bill does indeed drink — but the cause of his drinking is **not** his unhappiness. Uttered as two phrases, with an intonational boundary between '*drink*' and '*because*', it is more likely to convey that Bill does *not* drink — and that the reason for his abstinence is his unhappiness.

To characterize this phenomenon phonologically, we adopt Pierrehumbert's theory of intonational description for English (Pierrehumbert, 1980; Beckman and Pierrehumbert, 1986). In this theory, there are two levels of phrasing in English. An INTERMEDIATE PHRASE consists of one or more PITCH ACCENTS (local f0 minima or maxima) plus a PHRASE ACCENT (a simple high or low tone which controls the pitch from the last pitch accent of one intermediate phrase to the beginning of the next intermediate phrase or the end of the utterance). INTONATIONAL PHRASES consist of one or more intermediate phrases plus a final BOUNDARY TONE, which may also be high or low, and which occurs at the end of the phrase. Thus, an intonational phrase boundary necessarily coincides with an intermediate phrase boundary, but not vice versa. We employ Pierrehumbert's system also for our Spanish corpus, with modifications that do not affect the description of phrasing levels.

While we assume phrase boundaries to be perceptual categories, these have been found to be associated with certain physical characteristics of the speech signal. In addition to the tonal features described above, phrases may be identified by one of more of the following features: pauses (which may be filled or not), changes in amplitude, and lengthening of the final syllable in the phrase (sometimes accompanied by glottalization of that syllable and perhaps preceding syllables). In general, major phrase boundaries tend to be associated with longer pauses, greater tonal changes, and more final lengthening than minor boundaries. These generalizations appear to hold for both English and Spanish. In the Bell Laboratories Text-to-Speech system (TTS), intonational boundaries are realized by the manipulation of all of these features. However, currently, only intonational phrase boundaries are modelled in TTS, so this is the only level of phrasing we will discuss below.

2 Phrasing Prediction for Text-to-Speech

Most text-to-speech systems that handle unrestricted text rely upon simple phrasing algorithms based upon orthographic indicators, keyword or part-of-speech spotting, and simple timing information to assign phrase boundaries (O'Shaughnessy, 1989; Larreur, Emerard, and Marty, 1989; Schnabel and Roth, 1990). More sophisticated rule-based systems have so far been implemented primarily for message-to-speech systems, where syntactic and semantic information is available during the generation process (Young and Fallside, 1979; Danlos, LaPorte, and Emerard, 1986). However, general proposals have been made which assume the availability of more sophisticated syntactic and semantic information to use in boundary prediction (Altenberg, 1987; Bachenko and Fitzpatrick, 1990; Monaghan, 1991; Quené and Kager, 1992; Bruce et al., 1993), although no current proposal integrating such information into the process has been shown to work well even from hand-labeled input. And, even if such information could be obtained automatically and in real time for text-to-speech, such hand-crafted rules systems are notoriously difficult to build and to maintain.

Recently, efforts have been made to acquire phrasing rules for text-to-speech automatically, by training self-organizing procedures on large prosodically labeled corpora (Wang and Hirschberg, 1991a; Wang and Hirschberg, 1991b; Hirschberg, 1991; Wang and Hirschberg, 1992; Veilleux and Ostendorf, 1992). Such methods were used to train a phrasing module for the Bell Laboratories Text-to-Speech system from labeled speech from the DARPA ATIS corpus (Wang and Hirschberg, 1991a; Wang and Hirschberg, 1991b; Hirschberg, 1991; Wang and Hirschberg, 1992), which predicted intonational phrase boundaries correctly in just over 90% of cases, where data points were defined at the end of every orthographic word.

For this module, Classification and Regression Tree (CART) analysis (Breiman et al., 1984) was used to construct decision trees automatically from sets of continuous and discrete variables. In this case, these sets included values for all variables which appeared potentially useful in predicting phrasing decisions, and which could be acquired automatically from text analysis in real time.

To produce a decision tree, CART accepts as input a vector of all such independent variable values plus a dependent variable for each data point, and generates a decision tree for the dependent variable. At each node in the generated tree, CART selects the variable which best minimizes prediction error for the remaining unclassified data. In the implementation of CART used in this study (Riley, 1989), all of these decisions are binary, based upon consideration of each possible binary split of values of categorical variables and consideration of different cut-points for values of continuous variables. CART's cross-validated estimates of the generalizability of the trees it produces have proven quite accurate for the current task, when compared with tests on separate data sets; in every case CART predictions for a given prediction tree and that tree's performance on a hand-separated test set fall within a 95% confidence interval.[1]

This procedure performed fairly well, with results reported in Wang and Hirschberg 1992 of a CART cross-validated success rate of 90% correct classification of intonational phrase boundaries for trees grown using only information available automatically and in real time from text analysis. However, the hand-labeling required for the training data is enormously time-consuming and expensive, requiring well over one person-year to accomplish for the phrasing procedure described here. But automatic labeling of prosodic features does not appear to be reliable enough yet to serve as a substitute, despite some progress made in this area in recent years (Ostendorf et al., 1990).

2.1 Training Phrasing Procedures on Annotated Text

The current English version of Bell Labs TTS contains a phrasing module which was produced automatically, using procedures similar to those used in (Wang and Hirschberg, 1991a; Wang and Hirschberg, 1991b; Hirschberg, 1991; Wang and Hirschberg, 1992) to train phras-

[1]CART estimates are derived in (roughly) the following way: CART separates input training data into training and test sets (90% and 10% of the input data in the implementation used here), grows a tree on the training data and tests on the test data, repeats this process a number of times (five, in the implementation used here), and computes an average result for each subtree.

ing procedures on hand-labeled speech. However, the prediction tree in this module was itself trained not on prosodically labeled speech but upon a hand-annotated corpus of approximately 87,000 words of text taken from the AP newswire, and labeled for likely prosodic boundaries by a native speaker of standard American English. The use of such text training data cuts the time needed to train a new phrasing module from well over a year to just two or three days, by eliminating the costly hand-labeling of speech. Thus it is possible to retrain the existing TTS phrasing procedure quickly, as deficiencies are uncovered, by the simple addition of exemplars of the (corrected) behavior to the training set. It is also possible to produce phrasing procedures easily for new domains or languages without recording or labeling a large corpus. The Spanish phrasing procedure recently developed is a demonstration of this technique's versatility: a baseline version of this model which performed at about 90% correct was produced in only about a one and one-half person weeks.

To produce this phrasing procedure, or a phrasing procedure for a new application or domain or a new language, we proceed as follows: On-line text from an appropriate domain is first annotated with likely intonational boundaries by a native speaker of the language for which rules are desired. We are currently using newswire text from the English and Spanish AP for general TTS training purposes, but other text could be used for particular applications, for example. The unannotated version of the text is itself analyzed to extract values for features of each potential boundary site (defined as each position between two orthographic words $< w_i, w_j >$ in the input) which have been shown or appear likely to correlate with phrase boundary location — and which can be extracted automatically and in real time. For English, these features include:

- a part-of-speech window of four around the site, $< w_{i-1}, w_i, w_j, w_{j+1} >$;
- whether w_i and w_j are ACCENTED (intonationally prominent) or not;
- the total number of words in the utterance;
- the distance in words from the beginning and end of the utterance to $< w_i, w_j >$;
- the distance in syllables and in stressed syllables of $< w_i, w_j >$ from the beginning of the utterance;
- the total number of syllables in the utterance;
- whether the last syllable in w_i is strong or weak;
- the distance in words from the previous internal punctuation to w_i;
- the identity of any punctuation occurring at the boundary site;
- whether $< w_i, w_j >$ occurs within or adjacent to an NP;
- if $< w_i, w_j >$ occurs within an NP, the size of that NP in words, and the distance of $< w_i, w_j >$ from the start of the NP

For Spanish, the feature set currently includes only the part-of-speech window, whether or not w_i and w_j are accented or not, the total number of words in the sentence, the distance of the potential site from the beginning and end of the sentence in words and from the beginning of the sentence in syllables, the identity of any punctuation occurring at $< w_i, w_j >$, the distance of $< w_i, w_j >$ from the last punctuation mark, and whether or not vowel elision would occur across $< w_i, w_j >$.

Vectors of independent feature values plus the dependent "observed" value — is an intonational phrase boundary likely to occur at $< w_i, w_j >$ in the annotator's reading of the sentence or not — are then input to an implementation of CART (Riley, 1989). Note that the features described above represent only a subset of the features originally proposed to the automatic procedure; features which are not useful in prediction are simply ignored, and can be omitted from the final tree so that those feature values will not have to be obtained in text analysis in TTS. New features can be proposed to CART as readily as the requisite information can be obtained from the text. Features tested for English, which proved not to improve performance over those noted above, include: mutual information scores for words close to $< w_i, w_j >$ and structural syntactic information about constituents bordering on $< w_i, w_j >$ and immediately dominating that site.

For the phrasing module currently implemented in English TTS, a new matrix of feature vectors can be generated for new text simply by running TTS in training mode. The resulting tree is then compiled automatically into *c* code, which can be used for prediction itself in a stand-alone procedure, or which can be substituted for an existing decision tree module in the larger phrasing module.

3 Evaluation

Decision trees produced for English using annotated text for training perform somewhat better than trees trained on prosodically labeled speech, probably due to the increased size of the training set. The best result for English annotated text is a cross-validated score of 95.4% correct predictions on an 89,103 word training corpus, compared to around 90% cross-validated accuracy for the best trees trained on labeled speech. For Spanish, the best cross-validated success rate is 94.2% correct predictions of intonational phrase boundaries for a 19,473 word corpus.

To discover the main source of errors in phrasing predictions in the Spanish case, we evaluated the 1129 incorrect predictions reflected in the 5.8classified into felicitous and infelicitous. That is, if the proposed decision (presence or absence of an intonational boundary) resulted in a possible or grammatical reading of the sentence, it was classified as *felicitous*; and as *unfelicitous* if the resulting sentence was perceived to be unacceptable or ungrammatical. From the 1129 examples, 953 were in fact possible readings of the same sentence, which happened not to agree with the hand-annotated boundary locations. Also, we found 31 inaccurate labels in the original annotations: most of the cases corresponded to lack of boundary marks after orthographic commas or periods. The rest of the examples (only 145) were classified as unfelicitous. Thus, the initial 5.8rate in the Spanish case could be reduced to 0.74exclusively the decisions producing ungrammatical readings.

The 145 wrong predictions were then scrutinized. We note that the majority of the decision nodes base their judgment on the part-of-speech window feature. Part-of-speech classification was rather accurate: we found only 4 cases of POS classification error leading to ungrammatical predictions.[2] Also, 3 errors were due to the presence of preposed prepositional phrases, as in the following utterance: *En Madrid la gripe de este invierno...* 'In Madrid, the winter flu...'. Such detached phrases generally require a pause (or an intonational phrase-boundary tone) in between the prepositional phrase and the main clause, and they should be marked with a comma in the orthography. In the cases where the comma was not present, the special behavior of preposed prepositional phrases was not detected by our procedure, and no pause was predicted. Finally, the great majority of ungrammatical examples came from long stretches of words with no predicted pause, and which rendered the utterance almost unpronounceable. For some reason, the distance to preceding pauses was not selected by the decision procedure as an important factor to be considered.

Thus, we have detected two main sources of errors in the Spanish phrasing procedure. First, relatively minor errors in automatic procedures such as part-of-speech tagging and/or computation of distances to beginning and end of sentences. Second, a problem in the actual decision tree that causes most of the unfelicitous examples: the distance to previous pauses are hardly taken into account in the decision nodes. Obviously, the effort to improve the Spanish phrasing performance should focus on the the second problem. To increase the performance of the system in this respect, we have to first revise the consistency of our data: the training data might exemplify two reading strategies and/or tempos, allowing in some cases very long stretches of words with no internal pause. Another strategy is to retrain the system with specific cases exemplifying the desired behavior.

4 Conclusion

We have described a procedure for training intonational phrasing decisions for unrestricted text- to-speech on annotated text, using CART techniques to generate phrasing decision trees automatically. This procedure has been used to build a phrasing module which is incorporated in the English Bell Labs TTS system and has also been used to construct a stand-alone procedure for the Mexican Spanish version of this system, for eventual inclusion in the Mexican TTS system. The advantages of this procedure are several: It makes updating an existing phrasing procedure simple and rapid: One need only provide a new or additional set of annotated text. Observed phrasing errors can often be corrected simply by providing correctly annotated exemplars of the observed error. Phrasing for new domains can also be modeled easily, simply by annotating text for the new domain. And phrasing rules can be acquired for new languages easily, limited mainly by the tools for text analysis available for the new language.

[2] The three examples were the following: 1) The word *gamma* was classified as verb instead of noun in *los rayos gamma para...*; 2) The complex verb *conseguido conquistar* was classified as noun plus verb; 3) The adjective *norteamericanas* was labelled as verb.4) the verb *son* 'they are' was classified as a noun. In all 4 cases, the incorrect label lead to the prediction of an ungrammatical pause.

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