Morphological Decomposition Revisited:
Evidence from English and German speech-in-noise tasks

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Introduction

A major debate in the field of lexical access has been the treatment of morphology. Two classes of models can be defined in this regard – associative models (e.g. TRACE, MERGE), which posit that words are stored whole in the lexicon, and combinatorial models, which claim that morphemes are stored separately in the lexicon and combined during lexical access (e.g. Clahsen et al. 2001; Taft and Forster 1975; Taft 1988). This study seeks to investigate both phonetic and morphological effects simultaneously, by using an auditorily-based task, with stimuli that have been chosen with both morphology and phonetics in mind. We hypothesize that effects of morphology such as those found in previous studies using visual-based tasks will also be found using a speech-in-noise task, providing support for a combinatorial model of lexical access.

Research Questions

- Determine the extent to which morphological complexity affects language comprehension
- Compare context effects to previous results from speech-in-noise tasks
- Determine to what degree context effects in spoken word recognition apply across languages

Method

Materials The two stimulus sets (one German and one English) consisted of 150 nonwords and 150 words (half monomorphemic and half bimorphemic). All stimuli were of the form CVCCVC (where V includes short and long vowels as well as diphthongs), with stress on the first syllable. CVCCVC tokens were chosen because they are fairly common in both English and German, and they include both monomorphemes and bimorphemes. Word stimuli were selected from the CELEX (Baayen and Rijn 1993) database. Nonword stimuli were based upon the word stimuli such that the two sets were fairly phonemically balanced.

Several lexicostatistical measures were computed for each stimulus. For nonwords, two measures of phonotactic probability were calculated based on the method of Vitevitch and Luce (2004). For the words, two log-10 based frequency measures, (one based on word forms; the other based on lemmas), was computed following the method of Newman et al. (1997, 875, footnote 1). Two measures of neighborhood density were also calculated for the words — a phonological one, in which all words with an edit distance of 1 are treated as neighbors, e.g. *pat* has neighbors *pet* and *rat*, and a phonetic measure was also calculated, based on the confusion matrices from the nonword data. The phonetic measure treats *pet* as a closer neighbor to *pat* than *rat*, given that [æ] and [ɛ] are more highly confusable than [ɪ] and [p]

Participants 30 subjects were recruited from the University of Michigan for the English experiment. 32 subjects from the University of Konstanz, Germany, were recruited for the German experiment. All subjects reported no known hearing deficiencies.

Task Subjects listened to the recorded materials over headphones and typed in what they heard using standard orthography. Signal dependent noise was added to the stimuli according to the method described by Schroeder (1968).

Analysis The data was analyzed using the j-factor model of Boothroyd and Nittrouer (1988). The j-factor model assumes that phonemes are the basic unit of speech, and that phonemes are perceived independently (which has been shown to hold true most of the time; see Fletcher (1953); Allen (1994)). The probability of correctly identifying a given word (or nonword) can be calculated as the product of the probabilities of its constituent phonemes.

$$p_w = p_{C1}p_{V1}p_{C2}p_{C3}p_{V2}p_{C4} \tag{1}$$

where p_w is the probability of correctly identifying a word (or nonword). Assuming that phonemes are perceived independently, (1) can be rewritten as:

$$p_w = p_p^j \tag{2}$$

where j is the number of phonemes, and p_p is the geometric mean of the probabilities of each constituent phoneme. Rewriting (2), the quantity j can be empirically determined from confusion matrices by:

$$j = \frac{log(p_w)}{log(p_p)} \tag{3}$$

Predictions

$$\left.\begin{aligned} j_{nonword} &\approx 6 \\ j_{nonword} &> j_{word} \\ j_{word} &\propto \frac{1}{\text{frequency}} \\ j_{word} &\propto \text{density} \end{aligned}\right\}$$

These predictions based on Benkí (2003) and Boothroyd and Nittrouer (1988). Since j can be thought of as the number of independent units in a word, the facilatatory effect of higher lexical frequency should result in a lower j, while the competitive effect of a dense neighborhood should resulted in a higher j.

$$\left. j_{bi} > j_{mono} \right\}$$

This predicts that additional morphemes will add to the overall number of independent units of the word.

Results

The basic results are shown in Figures 1 through 4. Figures 1 and 2 provide subjects analyses, while figures 3 and 4 provide items analyses. The predicted differences between words and nonwords was robust in both the English and German data, as shown in figures 1 and 2.

Morphological Results Initially, there seems to be a discrepancy between the English and German data in terms of morphological effects on spoken word recognition. While there is a significant difference between monomorphemic and bimorphemic words in English, there is not in German. However, upon further inspection, it was found that the results from English are in fact misleading. It happened to be that the monomorphemic English words had a significantly higher lexical frequency than the bimorphemic English words, while the German materials had no such difference. To control for frequency, a subset of 65 English word stimuli (33 mono- and 32 bimorphemes) which were balanced for frequency was analyzed, and no significant difference was found. Also, in order to check statistical power, a random subset of 64 English words which differed in lexical frequency was also analyzed, and a significant difference was found. These results are shown in figures 5 and 6.

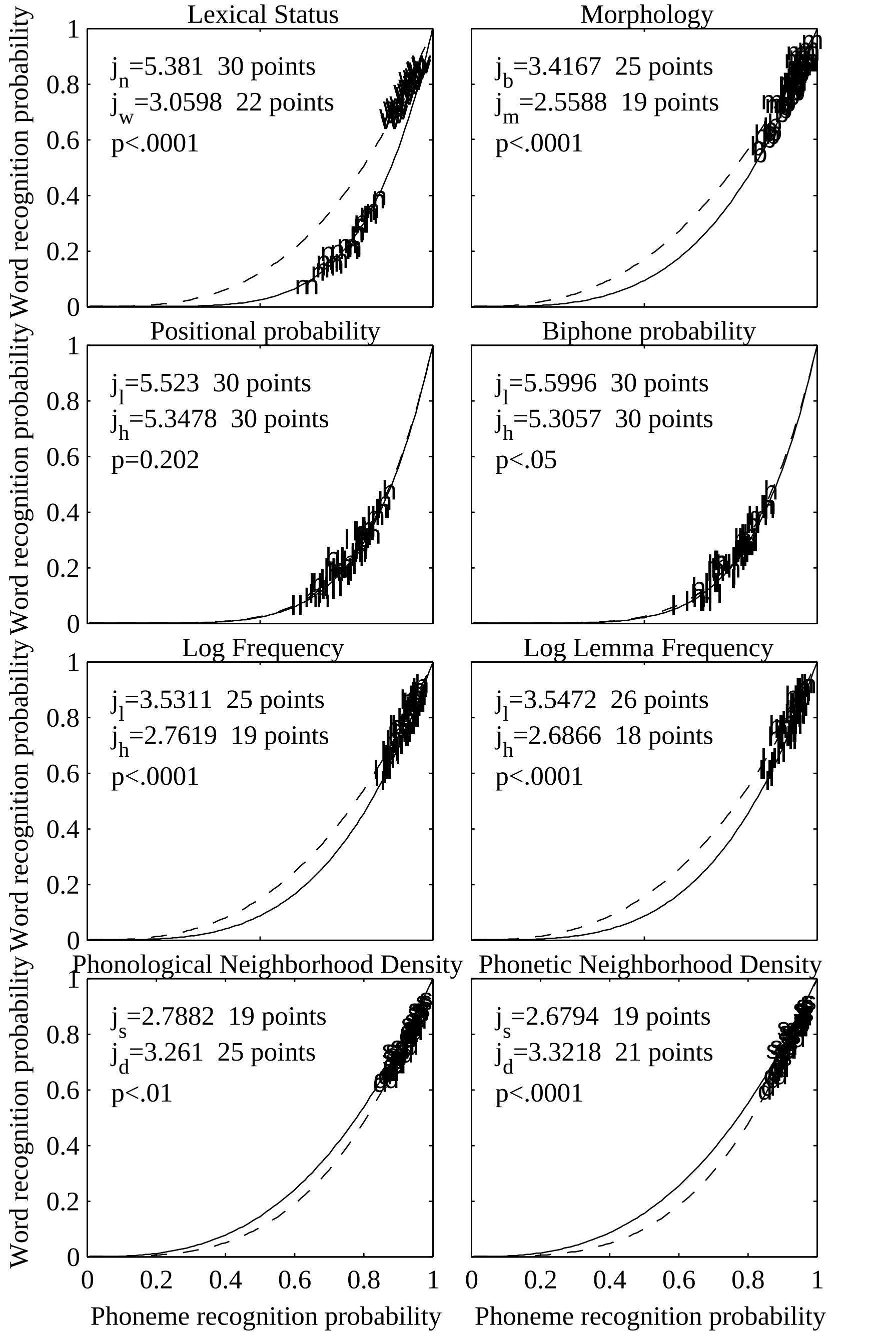

Figure 1: English J-Factor results - Each plot compares two subsets of results from the subject analysis. Curves represent $y = x^j$. The second row of plots only shows nonword results, while the final two rows only display word results. P-values given are from 2-sample t-tests; before computing the statistics, all points lying in the floor or ceiling ranges ($> .95$ or $< .05$) were removed, but are still shown on the plot.

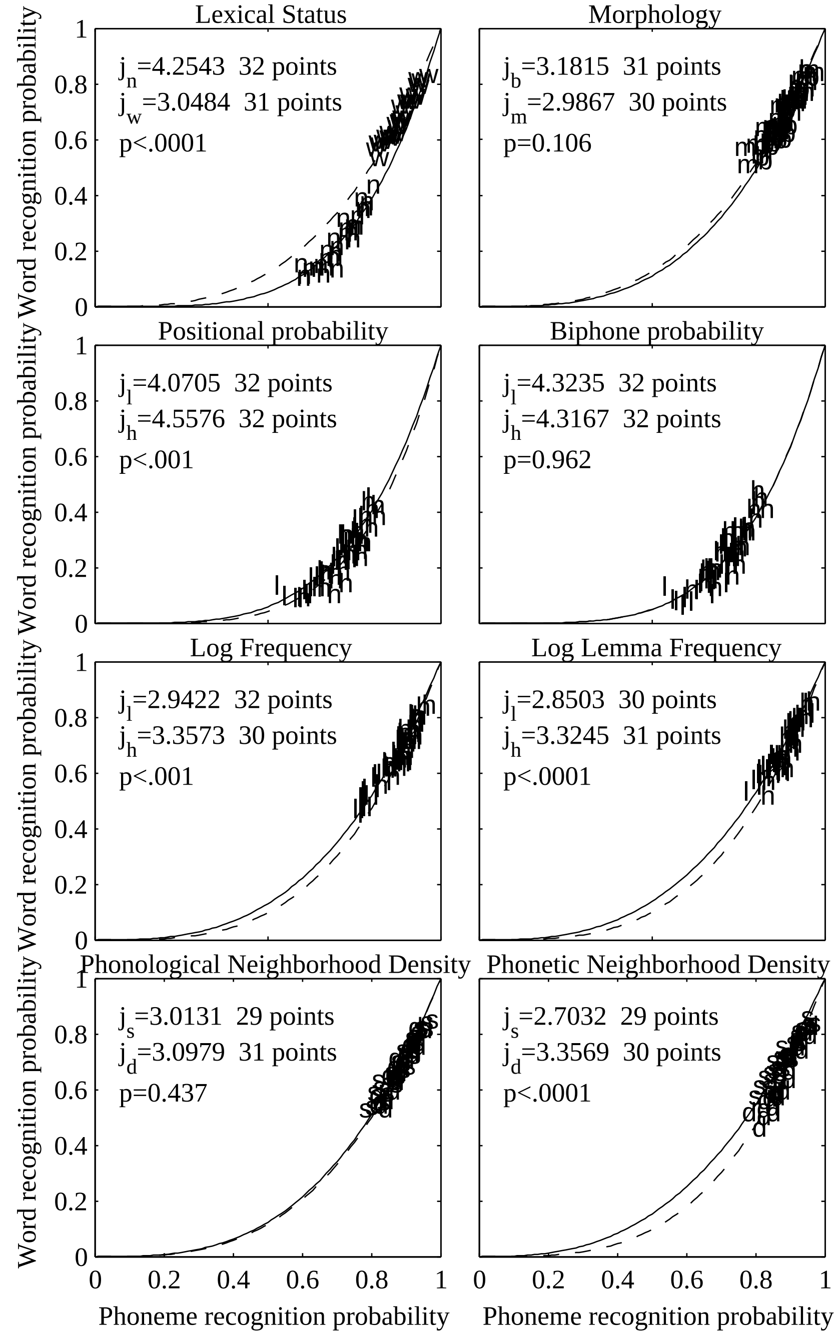

Figure 2: German J-Factor results - Each plot compares two subsets of results from the subject analysis. Curves represent $y = x^j$. The second row of plots only shows nonword results, while the final two rows only display word results. P-values given are from 2-sample t-tests; before computing the statistics, all points lying in the floor or ceiling ranges ($> .95$ or $< .05$) were removed, but are still shown on the plot.

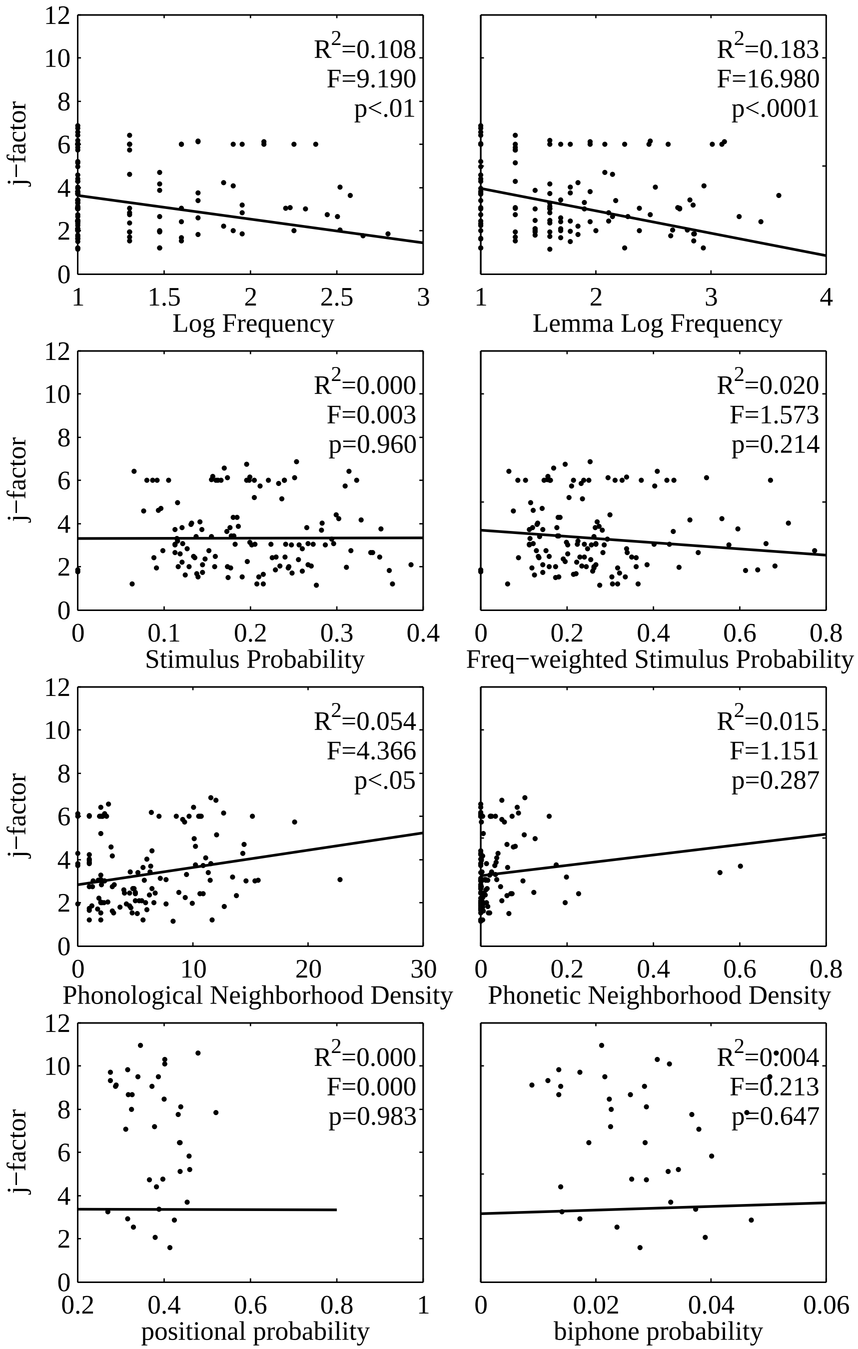

Figure 3: English J-Factor regression analyses. Each panel plots j-factor as a function of one particular lexicostatistical measure. Each point represents one item. The top 6 panels show only word items, while the bottom two show only nonword items. The statistics given are from linear regressions.

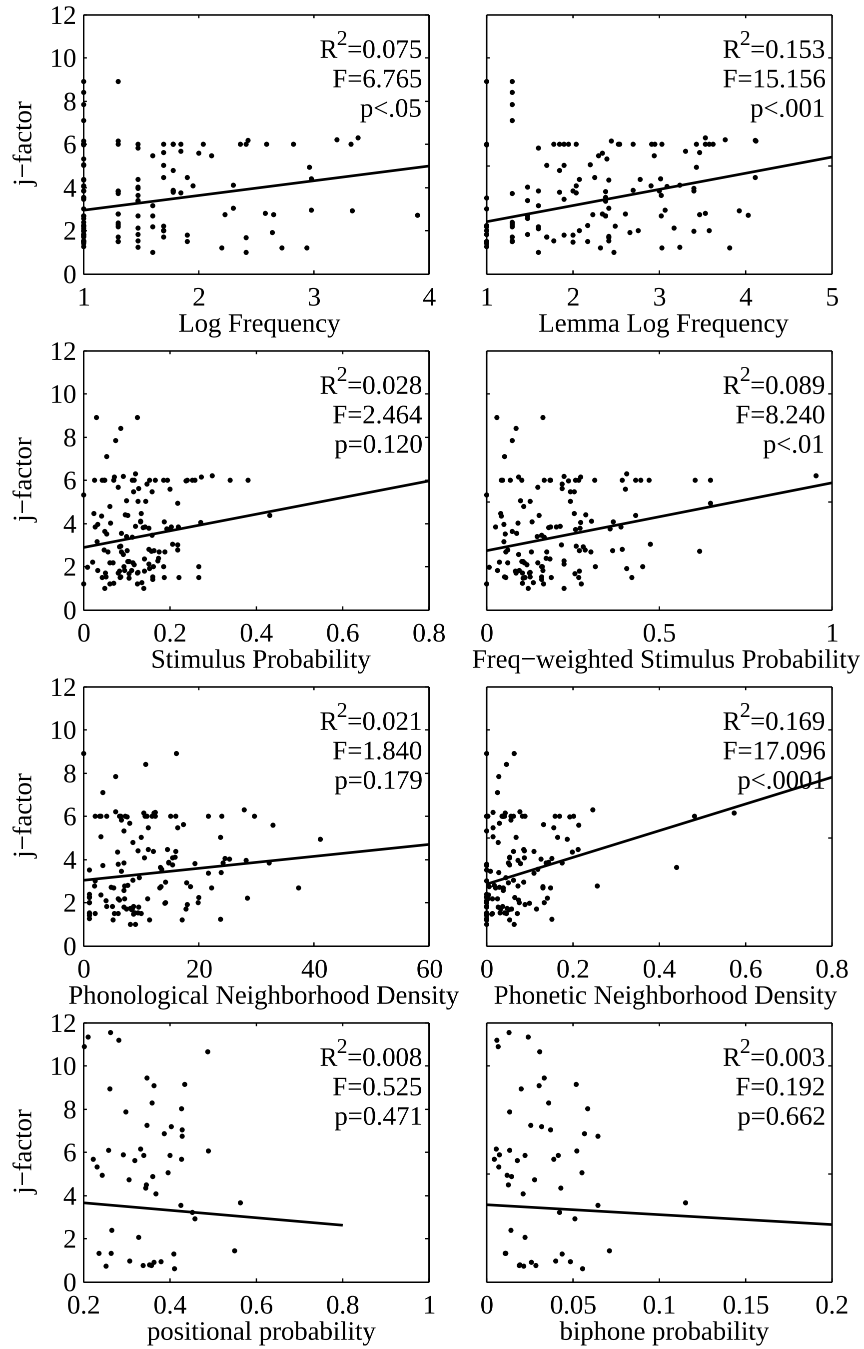

Figure 4: German J-Factor regression analyses. Each panel plots j-factor as a function of one particular lexicostatistical measure. Each point represents one item. The top 6 panels show only word items, while the bottom two show only nonword items. The statistics given are from linear regressions.

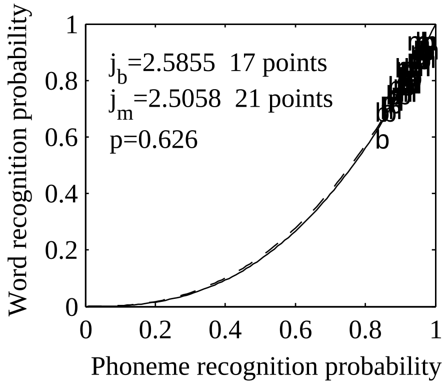

Figure 5: English experiment subjects analysis using a subset of the data matched for lexical frequency.

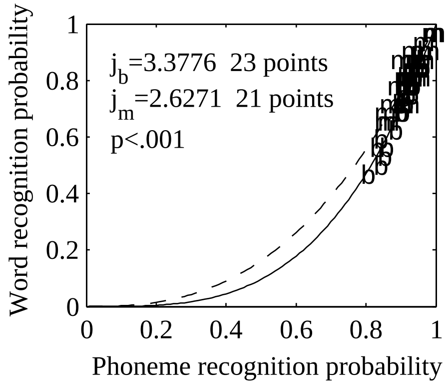

Figure 6: Same as Fig. 5 but using a random subset of the data in which the lexical frequency imbalance of the whole set was reflected.

Discussion

Context Effects Once controlled for other factors such as frequency, no significant difference was found between monomorphemes and bimorphemes in the subjects analysis. It should be noted however, that in the items analysis, j was more highly correlated with the lemma log frequency than the word form frequency, suggesting that perhaps morphemes are stored separately in the lexicon as Combinatorial Models suggest. It is certainly apparent that morphology has a relatively small effect on word recognition compared to other context effects such as frequency and neighborhood density.

Cross-language comparison The effect of lexical status was very clear for both the English and German experiments. The finding in English of $j_{nonword} \approx 5.38$ is fairly consistent with the predictions, and with prior research using CVC nonwords (e.g. Benkí 2003; Boothroyd and Nittrouer 1988)

The finding of $j \approx 4.25$ for German nonwords is substantially lower than predicted. One possible explanation for this could be that the German nonwords were more word-like than the English nonwords. According to the measures of phonotactic probability used, this is not the case, as the German nonword stimuli have comparable or slightly lower phonotactic probability scores than the English stimuli.

The result of $j_{word} \approx 3.05$ for both the German and English data provide a new finding for the field. Previous research (Boothroyd and Nittrouer 1988; Benkí 2003; Olsen et al. 1997) using CVC stimuli found $j_{word} \approx 2.5$. Bases on these results, one might expect j_{word} for CVCCVC stimuli to be approximately double that. It is clearly apparent however, that j_{word} does not scale linearly with word length.

One strikingly unexpected result is the positive correlation between lexical frequency and j for the German data — the opposite of the predicted result (and opposite from the English data). It appears that this effect is in fact due to a correlation ($r = .3594, p < .0001$) between phonetic neighborhood density and lexical frequency in the German data. Thus it seems that the effect of neighborhood density is overshadowing the effect (if any) of lexical frequency. This is in part consistent with Benkí (2003), who found neighborhood density to be a much stronger predictor of recognition than lexical frequency.

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