Sentences modulate the low-frequency neural response to words

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Listeners have the remarkable ability to combine acoustic information from speech with abstract linguistic knowledge, resulting in a structured representation of intended meaning. Recent work in psycho- and neurolinguistics has revealed signatures of this process in the brain: in the delta band (≤4Hz) – the timescale of occurrence of words and phrases in language – speech tracking is affected if the linguistic structure or content is manipulated (Blanco-Elorrieta et al., 2020; Molinaro & Lizarazu, 2018; Kaufeld et al., 2020). In the theta band (4-8 Hz), which corresponds to the timescale of syllables, speech tracking is affected by modifications of the acoustic signal (Blanco-Elorrieta et al., 2020; Etard & Reichenbach, 2019; Peelle, Gross & Davis, 2012; Doelling et al., 2014). Furthermore, lexical features also appear to be encoded in low-frequency neural responses (e.g., Weissbart et al., 2019; Brodbeck et al., 2018; Broderick et al., 2018). Yet, it is not clear how linguistic structure affects lexical encoding. Here we asked therefore how the neural response to words in the delta and theta bands changes, when spoken words appear in sentences or word lists.

We compared responses to words in MEG data from 102 participants listening to natural Dutch sentences (9 to 15 words) and word lists: scrambled versions of the sentences. The data are part of the MOUS-study (Schoffelen et al., 2019). We modeled the responses using temporal response functions (TRF). In TRF-estimation, we regress stimulus features on the neural signal at different time-lags, meaning that the stimulus is aligned to the neural signal at a 10ms delay, or at 20ms, et cetera. This yields a regression weight at each lag, capturing the neural response in a time-course: the TRF. The TRF is then used to reconstruct the MEG.

We estimated responses to words using *word frequency* as a feature. Word frequency is word-internal information, the value doesn't change as a function of context, and is numeric, making it suitable for this type of analysis. Being a multiple regression, TRFs allow estimation of effects *above and beyond* any physical or acoustic variation between the word lists and sentences by modeling it. We did this using *speech envelope* and *word onset* features. In addition, to distinguish effects of structure and meaning from contextually weighted statistical predictability, we included *surprisal* and *entropy*. Models with all combinations of the surprisal, entropy and word frequency features were created (Table 1). We estimated TRFs from -200ms to 800ms, and measured how well they reconstructed the neural signal. The TRFs for word frequency were compared between conditions using a cluster-based permutation test. Effects of condition and features on the reconstruction accuracy was probed using a linear mixed model (LMM; formula: $\mathrm{accuracies} \sim (\mathrm{frequency} + \mathrm{surprisal} + \mathrm{entropy}) * \mathrm{condition} + (1|\mathrm{subject})$)). Post-hoc t-tests were performed on the models 'Entropy/Surprisal' and 'All'.

In the delta band, the word frequency TRFs differed between conditions, with pronounced differences between 200 and 500ms [fig. 1a]. The LMM on reconstruction accuracy revealed an interaction between condition and frequency ($\beta=1.90*10^{-3}$, $SE=7.28*10^{-4}, t(1530)=2.60, p<0.01; \chi^2(1)=6.75, p<0.01$): adding the word frequency feature improved reconstruction accuracy more in sentences than in word lists [fig. 1b/c]. The post-hoc tests confirmed this (all $q<0.05$). In the theta band, the word frequency TRFs differed at ~100 and ~200ms [fig 2a]. The LMM showed a beneficial effect of word frequency in both conditions ($\beta=9.93*10^{-4}$, $SE=3.84*10^{-4}$, $t(1530)=2.58$, $p<0.01$; $\chi^2(1)=21.53$, $p<0.01$), that disappeared in the post-hoc tests (all $q>0.1$). There was no interaction effect [fig. 2b/c].

These results suggest that the delta-band neural response to words is modulated by its involvement in linguistic structures – information that is added by the brain to the sensory signal. That this difference persists when context-driven lexical features like entropy and surprisal are added, implies that language comprehension cannot rely solely on sequential prediction: the brain takes structural information into account when processing words. The findings are in line with analysis-by-synthesis accounts of language comprehension that capitalize on the symbolic and compositional nature of language (Martin, 2016; 2020).

Table 1. The features included in each of the fitted models. 'x' indicates that a feature is included.

S. env.: Speech envelope
W-ons.: Word onsets
W-freq.: word frequency
Entr.: entropy
Surpr.: surprisal

Model	Features				
	S. env.	W-ons.	W-freq.	Entr.	Surpr
Onset	x	x			
Frequency	x	x	x		
Entropy	x	x		x	
Surprisal	x	x			x
Frequency / Entropy	x	x	x	x	
Frequency / Surprisal	x	x	x		x
Entropy / Surprisal	x	x		x	x
All	x	x	x	x	x

Figure 1. Delta band results. Upper: (a) Word frequency TRF (solid: sentence; dashed: word list) & significant sensors at yellow time-lags. Lower left: (b) Reconstruction accuracies. Lower right: (c) Scalp map of t-values for reconstruction accuracies of 'All' vs 'Entropy/Surprisal' models split for condition.

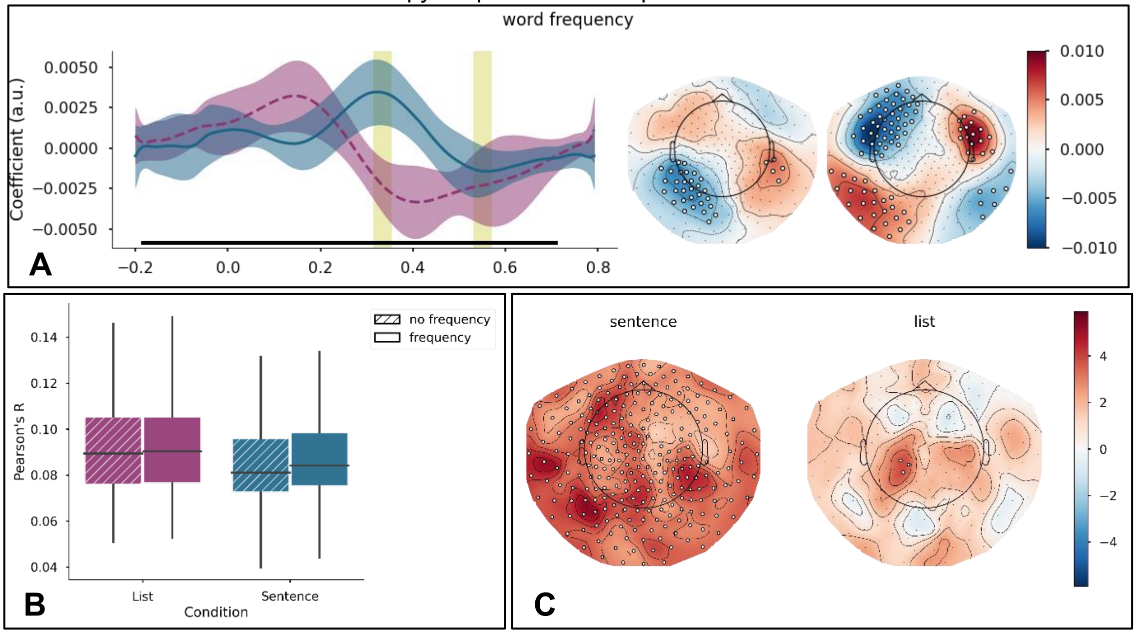
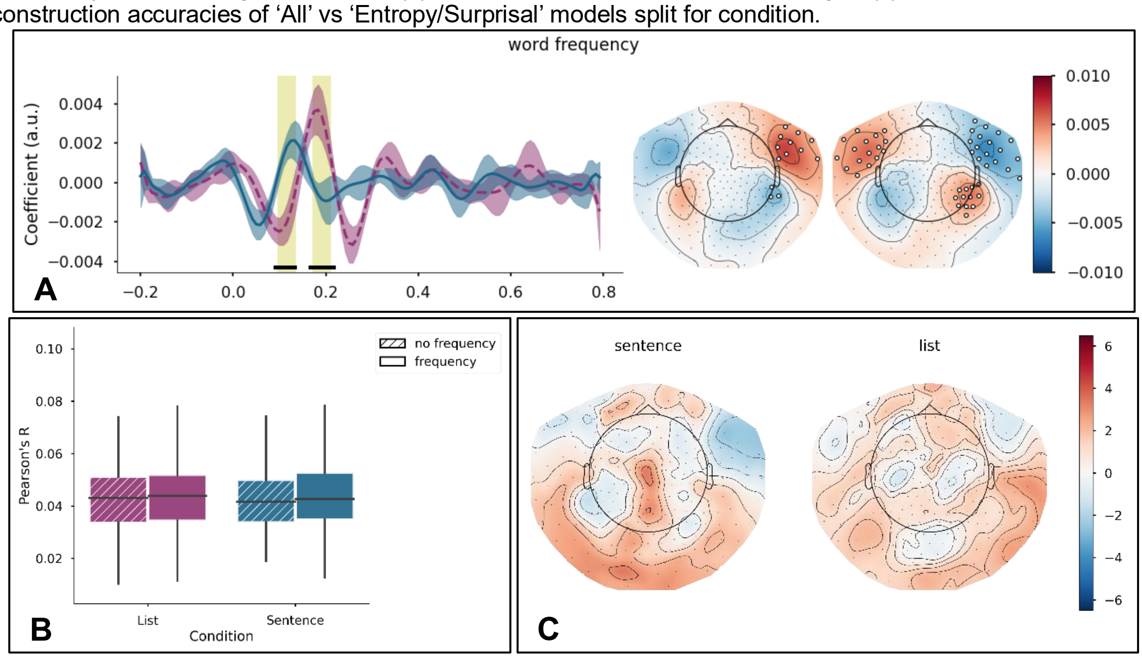


Figure 2. Theta band results. Upper: (a) Word frequency TRF (solid: sentence; dashed: word list) & significant sensors at yellow time-lags. Lower left: (b) Reconstruction accuracies. Lower right: (c) Scalp map of t-values for reconstruction accuracies of 'All' vs 'Entropy/Surprisal' models split for condition.



References

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