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CNL Disambiguating form and lexical frequency effects in MEG responses using homonyms

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We present an MEG study of homonym recognition in reading, identifying effects of a semantic measure of homonym ambiguity. This measure sheds light on two competing theories of lexical access: the "early access" theory, which entails that lexical access occurs at early (pre 200 ms) stages of processing; and the "late access" theory, which interprets this early activity as orthographic wordform identifcation rather than genuine lexical access. A correlational analysis method was employed to examine effects of the lexical frequencies of distinct words that share the same orthography (homographs) on brain activity. We find that lexical frequency did not affect processing until after 300 ms, while earlier activation was primarily modulated by orthographic form frequency.

Keywords: Lexical access; MEG; Visual word recognition; Homonym.

INTRODUCTION

Understanding spoken or written language is the process of transforming sensory stimuli into internal mental representations of meaning. A key component of this transformation is the connection of orthographic or phonological representations of words to their semantic referents. This process is often abstractly modeled as a kind of lexical access, in which a specific representation is selected from a lexicon of word meanings. The precise time-course of linguistic processing can be studied using neuroimaging techniques with high temporal precision such as EEG or MEG. The finding of a neural response that correlates with some semantic property of the word is often used as evidence that lexical access has begun by the time of that response. One such putative property is the frequency of the word in a language. Word frequency has been well established as a factor speeding response time in a variety of experimental tasks (Scarborough, Cortese, & Scarborough, 1977). While Embick, Hackl, Schaeffer,

Kelepir, and Marantz (2001) found reliable correlates to the behavioural latency effect in the latency of MEG M350 responses, others have also found word frequency effects in EEG N280 and N400 potentials and earlier MEG responses (Assadollahi & Pulvermüller, 2003; Hauk & Pulvermüller, 2004; King & Kutas, 1995). Although these may indeed reflect lexical access of some kind, in order to unambiguously identify signatures of access to a semantic lexicon, confounding factors that may give rise to correlations between semantic and abstract, form-based properties must be carefully considered.

Various manipulations have been done to try to resolve such confounds and identify semantically sensitive components of responses in order to locate lexical access in the course of word recognition. Frequency effects have been found using nonword letter stimuli, indicating that effects of word frequency may also be due to frequencies of component letters sequences. One fMRI study focusing on the visual word form area (VWFA) in which many of these effects have been localised showed no significant difference between frequent quadragrams and real words (Vinckier et al., 2007). Hauk, Davis, Ford, Pulvermüller, and Marslen-Wilson (2006) regressed EEG responses on correlates of various lexical properties of visually presented words, including a measure of semantic coherence based on the morphological family of each word. They found early effects of form frequency, by around 100 ms, and slightly later effects of a measure correlated with semantic coherence, concluding that lexical resolution happens between 100 and 170 ms. It should be noted, however, that their semantic coherence measure, based on a PCA, did correlate with various frequency measures and was found to have a much weaker effect than typical lexicality measures which peaked after 300 ms. On the other hand, Pylkkänen, Stringfellow, and Marantz (2002) provide evidence that the lexical process cannot have completed before 350 ms by manipulating two different but correlated semantic variables that affect behavioural lexical decision time. They found that phonotactic probability was associated with shorter M350 response latencies, while no effects were found from phonological neighbourhood density, which under early access theories should have an inhibitory effect on postsemantic processing. (For a more involved discussion of these issues, see Solomyak & Marantz, 2009a.)

The approach we employ to resolve this dilemma relies on a specific form of linguistic ambiguity: homographic homonymy, where distinct word meanings have identical orthographies, such as the verb and noun *peer*. These words allow form frequency to be disentangled from the frequency of individual meanings, which we will call *lexical frequency*. Solomyak and Marantz (2009a) developed a novel technique for making this comparison with MEG responses using nonhomophonic homographs (e.g., the verb *wind* and noun *wind*), disambiguating effects related to orthographic forms from those dependent on phonological resolution. They found early effects of form frequency on a response in the inferior occipitotemporal region (associated with the MEG M170) around 150 ms, while effects from the phonologically distinct lexical frequencies were only found at a much later response in the superior temporal and Sylvian Fissure region after 300 ms (MEG M350).

Homonymy is distinguished from another type of linguistic ambiguity known as polysemy, in which a single meaning has multiple related senses. There is evidence that these two types of ambiguity have distinct effects on processing, both in response time (Rodd, Gaskell, & Marslen-Wilson, 2002) and in the MEG M350 response (Beretta, Fiorentino, & Poeppel, 2005). There is also some evidence that homonyms have separate neural representations, each of which may cover many polysemic senses (Pylkkänen, Llinás, & Murphy, 2006; Tamminen, Cleland, Quinlan, & Gaskell, 2006).

These findings suggest that a semantic lexicon may have separate entries for homonyms representing the distinct meanings, but overlapping representations for polysemy within each entry. In one class of network models compatible with this concept, senses of a word are modelled as highly correlated feature sets, resulting in excitatory activation between senses of the same word, while distinct meanings have uncorrelated connections and thus inhibitory representations just as distinct words do (Rodd, Gaskell, & Marslen-Wilson, 2004). Under these models, the latency of a peak in network activation reflects the settling time of the network, while the magnitude reflects the extent of the activity, both of which will be increased by conflicting activations. Accordingly, when an isolated homograph is presented, all representations are initially activated, but activation will not peak until a single meaning entry is selected.

We thus attempted to verify such a model of the neural processes associated with visual word recognition by seeking neural correlates that were modulated by measures associated with these types of ambiguity. In particular, since homonyms have multiple distinct meanings, each meaning can be said to have its own frequency in the language, and these lexical frequencies will sum to the frequency of the shared form. Additionally, there is a range of ambiguity among homonyms from balanced, where all meanings are similarly likely as in *pawn*, to unbalanced, where one meaning is dominant as in *down*. Under the network interpretation, more balance among the meanings of a given homonym results in more competition between meanings, and thus more prolonged and stronger network activity. This is consistent with the many findings of meaning ambiguity disadvantage (Klepousniotou & Baum, 2007) and similarly suggests increased neural activity in resolving more balanced words.

In this study, we aimed to exploit these balance differences to clearly disambiguate lexical and word form frequency effects. We tested the effect of varying homographs along the meaning balance dimension while controlling for form frequency and other confounding factors. We looked for effects of this semantic distinction on the M130 and M170 MEG responses to visual words in previously identified letter string (LS) and visual word form (VWF) areas to determine whether frequency effects shown in this time range (100–200 ms) reflect semantic or form variation. The definition of the time windows and regions of interest was motivated by previous work distinguishing two different early response components to visual letter string stimuli, known as Type I and Type II. Type I responses are characterised by an early (around 100 ms) response in occipital visual areas and associated with visual processing common to multiple domains, while Type II responses are letter-specific and occur later (around 150 ms) in the left inferior occipitotemporal cortex (Tarkiainen, Cornelissen, & Salmelin, 2002; Tarkiainen, Helenius, Hansen, Cornelissen, & Salmelin, 1999). These responses have been distinguished in MEG by the time window and magnetic field patterns and confirmed by field direction in both single-source dipole and distributed source cortical models (Solomyak & Marantz, 2009b), and are generally consistent with localisations of early ERP responses (Hauk et al., 2006).

To quantify ambiguity, we used a measure of meaning entropy introduced by Twilley, Dixon, Taylor, and Clark (1994) which represents the information content of a meaning resolution and reflects the amount of meaning balance. The entropy of a word with high meaning dominance, in which one meaning is far more prevalent than others, will be low, whereas that of a word with more balance will be higher, and will scale as the log of the number of balanced meanings. Thus, any response sensitive to the semantics of a word is predicted to show increased activity and latency with increasing entropy. Since a measure of true relative lexical frequency was unavailable,
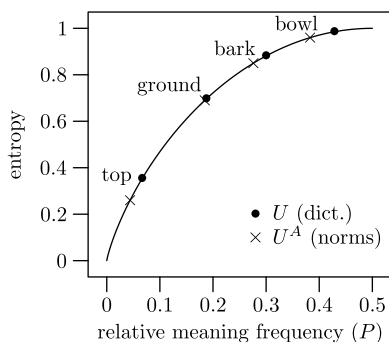
Figure 1. *Entropy function.* Example entropy values for words with two meanings, based on relative frequency of less common meaning as proportion of total form frequency. Dictionary-based approximations calculated for this study are shown along with sample norms from Twilley et al. (1994).

the proportion of dictionary senses within each meaning was used as a substitute for this value. This same number of senses count was shown to have the correct correlations with frequency, as well as a direct advantage for lexical access independent of frequency in earlier results (Rodd et al., 2002). Most importantly, it is a purely semantic measure, and so even if it fails to capture the appropriate frequency effects, a positive result must still reflect semantic resolution.

METHODS

Participants

Thirteen right-handed native English speakers (eight female) with normal or corrected-to-normal vision participated in the experiment. The participants were at or above the undergraduate level and were presumed to be normal readers. All

TABLE 1
Statistics of and correlations between the measures of interest across the 500 words (220 for U^A)

Statistics		L	B	F	M	S	U	U^A
Mean		4.222	2,141	8.660	2.234	8.216	0.929	0.733
SD		0.882	1,101	1.478	0.536	4.694	0.312	0.467
Min		3	75	6.3	2	2	0.310	0
Max		6	6,547	14.3	5	30	2.236	2.08
Bigram frequency, B	0.537						*Correlations*	
Log frequency, F	−0.111	0.032						
Meanings, M	−0.063	−0.004	0.019					
Senses, S	−0.044	−0.011	0.403	0.227				
Estimated entropy, U	−0.016	0.040	−0.128	0.815	−0.032			
Normed entropy, U^A	0.007	−0.038	0.036	0.202	0.087	0.160		
Parts of speech	−0.013	0.003	0.275	0.094	0.386	−0.037	−0.030	
Orthographic neighbourhood size	−0.767	−0.202	0.167	0.105	0.106	0.045	0.061	
Orthographic neighbourhood frequency	−0.528	−0.184	0.132	0.080	0.143	0.035	−0.003	
Cohort size	−0.153	−0.007	0.481	0.029	0.485	−0.113	−0.066	
Cohort frequency	−0.067	0.050	0.410	−0.009	0.204	−0.038	0.011	

Notes: L = length; B = bigram; F = form frequency; M = total meanings; S = total senses; U = entropy.

participants gave informed consent and received \$15 for their participation. The study was approved by the New York University Committee on Activities Involving Human Subjects.

Materials

The stimuli consisted of 500 homographic English words (between 3 and 6 letters long) and an equal number of length-matched nonwords. Word lists and properties were collated from the English Lexicon Project (Balota et al., 2002) and Wordsmyth Online Dictionary (Parks, Kennedy, & Broquist, 1998). For each word, we used the following measures from the English Lexicon Project: length in characters (L), summed bigram frequency (B), and log frequency in the HAL corpus (F). From the Wordsmyth Online Dictionary we extracted: the number of meanings (M) as the count of dictionary headword entries, and the number of senses within each meaning (S_m). All words were monomorphemic with no alternate spellings, phrasal dictionary entries, irregular capitalisation, or acronyms. We also determined the morphological family (cohort) size and summed frequency across all entries in CELEX (Baayen, Piepenbrock, & Gulikers, 1995) containing the word as a root.

Given the number of meanings for each word, M_n, and the number of senses for each meaning, $S_{n,m}$, we used the sense counts to estimate the relative frequencies for each meaning, and then used these frequency estimates to define our entropy estimate:

$$S_n = \sum S_{n,m}$$

$$P_{n,m} = \frac{S_{n,m}}{S_n}$$

$$U_n = -\sum P_{n,m} log_2 P_{n,m}$$
$$= log_2 S_n - \sum P_{n,m} log_2 S_{n,m}$$

where all sums are over the M_n meanings, m. The resulting U measures ranged from 0.31 (*hold*) to 2.24 (*mole*). Of these words, 220 were also included in the data collected by Twilley et al. (1994), which derived a similar measure of entropy from subject-reported associations, which we designate U^A. U^A and U were found to correlate significantly, $r(218) = .160$, $p = .018$. Some sample values for 2-meaning words are shown in Figure 1. Statistics for all the measures are included in Table 1.

Task

The participants were outfitted with five head position indicator (HPI) coils, and their head shape, fiducial locations, and HPI coil locations were digitised before the lexical decision task. Participants lay in a dimly lit magnetically shielded room while the visual words were presented in pseudorandom order. The task was a continuous lexical decision task, in which the word or nonword stimulus was presented, prompting the subject to make a decision about lexicality and to press a button with the left index finger to respond "yes" or with the left middle finger to respond "no". Stimuli were presented in lowercase, nonproportional Courier font, and subtended an average of $1.28°$ visual angle horizontally and vertically per character. Behavioural response times and accuracy data on the lexical decision task were collected for each participant. During the task, neuromagnetic fields were recorded continuously by a 157-channel axial gradiometer whole-head MEG system (Kanazawa Institute of Technology, Kanazawa, Japan) at a 1,000 Hz sampling rate. As part of

a separate session associated with a different experiment, a high-resolution T1-weighted anatomical MRI (MPRAGE sequence, $1 \times 1 \times 1$ mm) was obtained for each subject using a 3T Siemens Allegra head-only scanner. All acquisition was performed at the Center for Brain Imaging at New York University.

Analysis

The MEG data preprocessing steps were the same as those described in Solomyak and Marantz (2009a, 2009b) and Lewis, Solomyak, and Marantz (2011). First, raw data from 156 sensors were noise-reduced using data from three reference sensors located away from the subjects' heads and the Continuously Adjusted Least-Squares Method (CALM; Adachi, Shimogawara, Higuchi, Haruta, & Ochiai, 2001) in Meg160 software (Yokogawa Electric Corporation and Eagle Technology Corporation, Tokyo, Japan). The noise-reduced MEG, head shape digitisation, and sensor location data were imported into MNE (MGH/HMS/MIT Athinoula A. Martinos Center for Biomedical Imaging, Charleston, MA) for additional processing. Subjects' structural MRIs were reconstructed with the FreeSurfer software (CorTechs Labs Inc., LaJolla, CA). The data were then processed in MNE for estimation of each subject's cortically constrained minimum-norm solution. Next, a source space consisting of 5,124 activity points was created on each subject's reconstructed cortical surface. At each source, activity was computed for the forward solution with the BEM (boundaryelement model) method, which provides an estimate of each MEG sensor's magnetic field. The forward solution and the grand average activity across all trials and subjects were used to compute the inverse solution, which estimates the most probable distribution of averaged MEG data across space and time. The data were next converted into noise-normalised dSPM (dynamic statistical parameter map) values (see Dale et al., 2000). The brain of each subject was morphed to a standard FreeSurfer brain, and activity from all trials and subjects were averaged and projected on the standard brain. Regions of interest (ROIs) were then functionally defined on the standard inflated cortical surface, based on peaks in the grand average left hemisphere activation. ROI vertices were stored in label files and then morphed back to each subject's brain. For each subject, an inverse solution was computed for that subject's ROI across all trials.

The M130 ROI was identified based on a peak in average negative activity (current directed inward on the cortex) in the posterior occipital region, consistent with Type I activity. The M170 ROI was based on a peak in average positive activity (directed outward) in the left-hemisphere occipitotemporal fusiform gyrus region between 150 and 210 ms poststimulus onset. Lastly, the M350 ROI was based on grand average negative activation peaking around 300–370 ms in the lefthemisphere superior temporal and Sylvian Fissure regions. An extreme value count for each trial was made of data points with values falling two standard deviations from the overall mean. Trials were excluded from the analysis if their extreme value count exceeded the overall extreme value mean by more than three standard deviations.

For each ROI, the (directionally signed) activation from the MNE solution was averaged over the entire region to produce a time-course for each trial. In order to identify a representative time-course and peak response regions, the resulting time-courses were averaged over all included trials, and then over all subjects, thus timing was defined in absolute terms rather than relative to individual peaks. The time period around each peak during which the average response was within 5% of the total response range of the peak was selected for analysis. Within each included trial, the
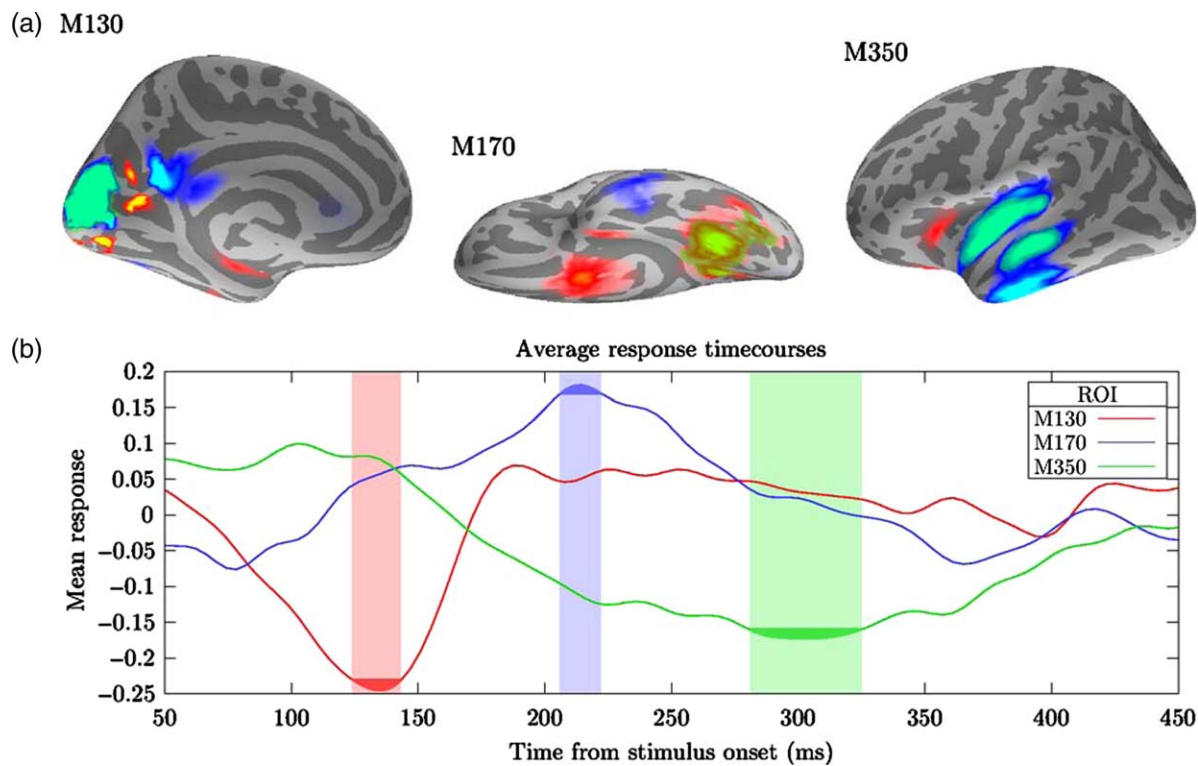
Figure 2. (a) Selected regions of interest and (b) average response across subjects across included trials across each region. Indicated time ranges are analysed peak regions having average response within 5% of peak. [To view this figure in colour, please visit the online version of this Journal.]

activation was averaged across this time period to get a single response amplitude per trial per region.

Standard group regressional analyses were used for behavioural and neural data, treating the first-level beta values as random variables, and testing whether the average response to each variable was significantly nonzero. The first-level design matrices consisted of the following regressors: a normalising constant, word length L, bigram frequency B, form frequency F, total meanings M, total senses S, and entropy U. The regressors were orthogonalised in this order, thus L was only mean-corrected and U had the projection of all the other regressors removed, and finally normalised to have unit variance for comparison between regressors. All trials with nonwords, incorrect ("no") responses, or response times over 2 seconds were excluded. For the response times only, in order to provide a more straight-forward interpretation, a fixed-effects analysis was also run, in which data from all subjects were entered into a single correlation, thus pooling variance across subjects (as in an items analysis) as well as items. All of these analyses were then repeated with regenerated regressors for the subset of words with U^A measures available. Finally, in order to assess changes in response magnitude between ROIs and variables for significant neural responses, we extended the regression analysis by applying an ANOVA to the first-level beta values. Specifically, for the M130 and M350 ROIs, we selected relevant pairs of variables and entered these into two-way (2×2) repeated-measures ANOVAs with ROI and variable as the factors.

RESULTS

Behavioural

Overall response accuracy was 92.9%. One subject had an accuracy rate of 77%, with the remaining subjects all performing over 90%. Fewer than 2% of trials were excluded for excessive response times over 2 seconds. In total, 5,063 trials were included for analysis. Of these, 2,298 had U^A values available.

Mean response time was 711 ms with a standard deviation of 233 ms. There was a significant inhibitory effect of U on response time, $t(12) = 2.91$, $p = .013$. There was similarly a significant effect of U^A on response time, $t(12) = 3.48$, $p = .0046$. Under a fixed-effects model, the effect of U was marginal, $r(5,061) = .026$, $p = .06$, and U^A was significant, $r(2,296) = .064$, $p = .0023$. There were also significant facilitatory effects of: F: $t(12) = -6.27$, $p = .0004$; M: $t(12) = -3.53$, $p = .004$; and S: $t(12) = -4.25$, $p = .001$. By reversing the orthogonalisation order of M and S, we found that the total number of senses explained the significant modulation by meaning as well: S: $t(12) = -5.14$, $p = .002$; M: $t(12) = -1.72$, $p = .11$, n.s.

Neural

After behavioural exclusions, an additional 73 trials were excluded from analysis based on MEG response characteristics. Based on average distributed source activity peaking at 133 ms in the left occipital cortex, the M130 ROI was defined over 4,448 vertices, with a peak activity period of 124–143 ms. Identified responses in the occipito-temporal fusiform gyrus peaked at 211 ms, used to define the M170 ROI covering 6,212 vertices and spanning 206–223 ms. Finally, the superior temporal M350 ROI covering 4,963 vertices was defined based on activity at the peak latency of
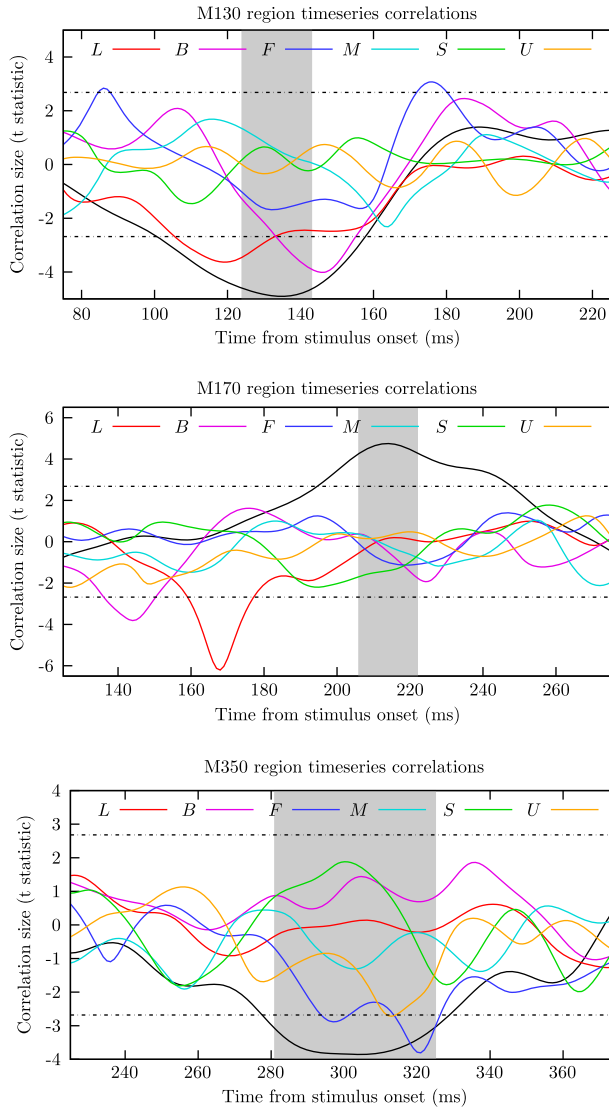
Figure 3. Group correlation statistic timeseries from regressions of each individual timepoint on length (*L*), bigram frequency (*B*), form frequency (*F*), number of meanings (*M*), number of senses (*S*), and meaning entropy (*U*). Also shown are the original average response (black curve, as in Figure 2) and $p = .01$ (uncorrected) significance levels (dashed line). [To view this figure in colour, please visit the online version of this Journal.]

315 ms, the peak was found at 304 ms, and the period spanned 281–325 ms. The defined ROIs and average response time-courses are shown in Figure 2.

Within the M130 activation, only word length and bigram frequency were found to have significant effects on response amplitude, $t(12) = -2.84$, $p = .015$, and $t(12) = -2.99$, $p = .011$, while word form frequency approached significance, $t(12) = -1.90$, $p = .082$, and no other effects were significant (all $p > .5$). Within the M350 activation on the other hand, form frequency and entropy both had significant effects, $t(12) = -3.16$, $p = .0082$ and $t(12) = -2.34$, $p = .037$, while no other variables were significant (all $p > .25$). All of these significant effects indicate increased
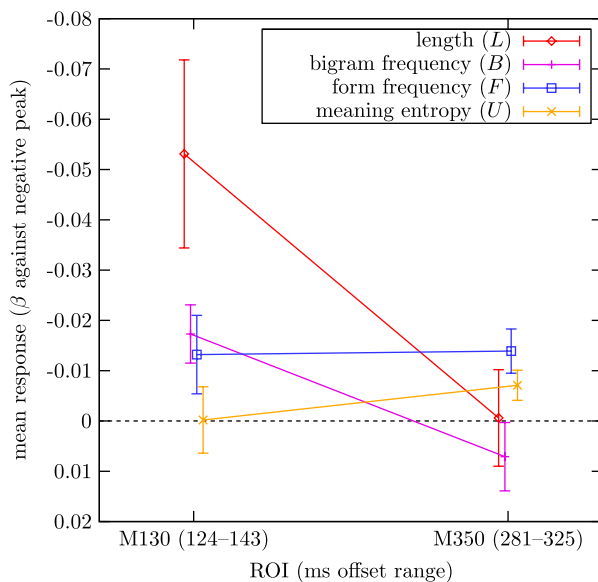
Figure 4. Interaction of significant responses between M130 and M350 ROIs. [To view this figure in colour, please visit the online version of this Journal.]

magnitude (negative) activity with increased frequency and entropy. Using only the reduced data set for which U^A was available, this pattern of results held, except the effect of U^A on M350 amplitude did not reach significance, $p = .085$. None of the M170 correlations was found to be significant (all $p > .2$); however in a post hoc test, recognising that our identified window was later than the M170 is commonly identified, we repeated the analysis at a single timepoint offset of 170 ms and found a significant effect of length only, $t(12) = -5.37$, $p = .0002$, with no significant effect of frequency, $t(12) = 1.13$, $p = .278$, or other variables (all $p > .5$). Within- and between-subject permutation tests on both the whole design matrix and the entropy measures alone validated these significance levels (within .005).

Repeating this analysis for each timepoint individually also revealed more details about the timecourse in a more traditional correlational analysis (Figure 3). In comparing the significant effects between ROIs and variables, we found significant ROI by variable interactions for M130 and M350 only with length and entropy, $F(1, 12) = 6.22$, $p = .028$, bigram frequency and form frequency, $F(1, 12) = 6.15$, $p = .029$, and bigram frequency and entropy, $F(1, 12) = 11.20$, $p = .006$, each such that L and B were stronger in the M130 compared to U, which was stronger in the M350 (Figure 4).

DISCUSSION

Many putative semantic measures that have been used to study the time-course of lexical resolution may also reflect abstract or syntactic properties of the language. Word frequency, for example, can be derived from observed form frequency without necessitating a meaning-based lexical representation. By parametrically varying a measure that is inherently dependent on semantics and independent of other word-form measures we can help disambiguate semantic and purely orthographic effects. The measure we used was based on the relative predominance of the distinct meanings of homographic homonyms, in terms of elicited frequency or number of senses, and

assumes that these meanings are relevant in some way to a lexical representation (e.g., as distinct representations in some type of lexicon). Entropy is an information-theoretic measure of uncertainty, or the amount of information (in bits) required to identify a particular meaning of a word from its ambiguous visual representation. Lexical resolution as we conceive it refers to resolving the meaning or meanings of a word, and thus we expected that this value would have correlates in the neural processes implementing this resolution.

While our behavioural results confirmed the general finding that ambiguity is advantageous in word recognition, with more senses resulting in shorter response times, we only weakly replicated the behavioural results of Rodd et al. (2002) in finding that homonymy had no significant effect after controlling for this effect of polysemy. After adjusting for these measures, we found that the entropy measure was relevant and inhibitory of word recognition, with higher entropy resulting in longer response times. We identified neural correlates of visual word recognition using MEG and focused on three distinct time and brain areas (ROIs) thought to participate in this process, associated with the M130, the M170, and the M350 MEG responses. Looking for parametric effects of our various measures in the amplitude of these responses, just as we did with response time, we found that, while the early M130 response was sensitive to form measures, the M350 activation uniquely showed effects of entropy.

These results are evidence that visual word processing involves some meaning-based resolution beginning around 300 ms after visual word presentation, or 160 ms after early neural responses. This implies that previously observed effects on earlier responses may be due solely to orthographic properties that are derivable from the letter sequence itself. However, the observed paired increase in semantic and decrease in form effects between earlier and later responses cannot prove the absence of semantic effects in the underlying neural activity or that some type of lexical access has not begun already. In particular, our data do not speak to the existence or role of independent phonological and orthographic lexicons during visual word recognition. Nevertheless, when taken with other findings of this nature (Lewis et al., 2011; Solomyak & Marantz, 2009a), these data do give weight to the assertion that M350 activity is the first to show strong semantics effects indicative of meaning resolution. The latency and localisation findings are also broadly consistent with other studies, including Beretta et al. (2005), which used a similar MEG paradigm and found effects of semantic ambiguity on the M350 response. Hauk et al. (2006) found the same relative order of effects and involved brain regions in an EEG study, supporting a model of early orthographic word form processing in occipitotemporal regions followed later by lexical access in superior temporal areas, although their particular semantic measure was found at an earlier absolute time, where we found no effects (in our M170 ROI). Finally, studies of semantic ambiguity using fMRI with sentence stimuli have found effects in left temporal regions as well and suggest that frontal regions may be relevant for further targeted MEG studies (Rodd, Davis, & Johnsrude, 2005; Mason & Just, 2007; Zempleni, Renken, Hoeks, Hoogduin, & Stowe, 2007).

While an appropriately controlled significant correlational finding is compelling regardless of the type of effect, the signs of the correlations are relevant to the network model. As predicted, we saw larger magnitude M350 activity to higher-entropy words, which implies that ambiguity introduces more inhibitory activity in the network, thus lengthening settling time and increasing net activity. This is consistent with the behavioural results. On the other hand, we also saw increasing activity to words with higher form-frequencies. This is contrary to the predictions of the simple network model, which stipulates that the baseline activity or prior probability for higher-

frequency words is higher, thus requiring less evidence to activate and resulting in a faster resolution, as evidenced by the response time. However, it has also been found that M350 activity increases with morphological family frequency (Pylkkänen, Feintuch, Hopkins, & Marantz, 2004), which makes sense within a network model framework as it provides a measure of the number of prospective nodes that may receive activation by the target word. This is also consistent with the findings of Lewis et al. (2011), which indirectly controlled for family size by using words with essentially no morphological families and found the traditional facilitatory effect of frequency, with reduced M350 activity for higher frequency bases. Indeed, when we considered the effect of cohort measures, we found an increase in M350 activity with increasing family size or frequency, but no significant effect of frequency after removing the variance explained by either of these variables (data not shown), similar also to the findings of Solomyak and Marantz (2009b). Overall, our results support late access network models of semantic resolution and open the door for further studies of the precise mechanisms of lexical resolution and semantic disambiguation.

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