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Brain networks associated with sublexical properties of Chinese characters

Jianfeng Yang^a, Xiaojuan Wang^b, Hua Shu^b, and Jason D. Zevin^{c,*}

^a Key Laboratory of Behavioral Science, Institute of Psychology, Chinese Academy of Sciences, China

^b State Key Laboratory of Cognitive Neuroscience and Learning, Beijing Normal University, China

^c Sackler Institute for Developmental Psychobiology, Weill Cornell Medical College, USA

Abstract

Cognitive models of reading all assume some division of labor among processing pathways in mapping among print, sound and meaning. Many studies of the neural basis of reading have used task manipulations such as rhyme or synonym judgment to tap these processes independently. Here we take advantage of specific properties of the Chinese writing system to test how differential availability of sublexical information about sound and meaning, as well as the orthographic structure of characters, pseudo-characters and “artificial” control stimuli influence brain activation in the context of the same one-back task. Analyses combine a data-driven approach that identifies temporally coherent patterns of activity over the course of the entire experiment with hypothesis-testing based on the correlation of these patterns with predictors for different stimulus classes. The results reveal a large network of task-related activity. Both the extent of this network and activity in regions commonly observed in studies of Chinese reading are apparently related to task difficulty. Other regions, including temporo-parietal cortex, were sensitive to particular sublexical functional units in mapping among print, sound, and meaning.

Keywords

fMRI; Reading; Visual word recognition; Chinese character recognition; Independent component analysis

Reading is a complex skill involving the coordination of multiple brain processes that draw upon sources of information including abstract visual properties of print (orthography), knowledge of the pronunciations (phonology) and meanings (semantics) of printed words (Rayner, Foorman, Perfetti, Pesetsky, & Seidenberg, 2001). Neuroimaging studies of reading thus reliably reveal a broad network of brain regions that are plausibly related to higher visual processing (occipito-temporal cortex, or the “visual word form area”), phonological processing (posterior portions of middle and superior temporal and opercular inferior frontal gyrus) and semantic processing (triangular inferior frontal gyrus, see review in, e.g., Price, 2000).

This preponderance of data has begun to provide important insights about how the neurobiology of the reading system might be related to contemporary cognitive models of

reading (Jobard, Crivello, & Tzourio-Mazoyer, 2003; Pugh et al., 2000). For example, Frost et al. (2005) observed an interaction among frequency, consistency and imageability, and a trade-off between regions associated with phonological and semantic processing. This fits within a general model of reading (Harm & Seidenberg, 2004; Seidenberg & McClelland, 1989) in which the “division of labor” between semantic and phonological processing is modulated by different stimulus properties. On this view, words with more difficult spelling to sound mappings require more input from semantics to be read quickly and accurately, and therefore show greater influence of semantic variables. Thus, greater involvement of brain regions involved in print-to-meaning mappings is to be expected for stimuli with more difficult print-to-sound mappings.

Another approach to understanding the brain basis of reading has been to conduct analysis based on effective connectivity among networks (e.g., Bitan, Cheon, Lu, Burman, & Booth, 2009; Cao, Bitan, & Booth, 2008; Pugh et al., 2000). This approach has the advantage of considering the coordinated activity of multiple regions, rather than attempting to understand single regions in isolation (e.g., Horwitz, Rumsey, & Donohue, 1998; Penny, Stephan, Mechelli, & Friston, 2004; Skipper, Goldin-Meadow, Nusbaum, & Small, 2009). Many studies combine this technique with task manipulations designed to tap interactions between different component processes of reading. For example, Bitan et al. (2005) identified regions commonly activated by spelling and rhyming tasks and regions selectively activated by one or the other. They then showed that the strength and direction of connectivity among orthographic and phonological processing regions was modulated by task.

In both the Frost et al. (2005) and Bitan et al. (2005) studies, the analyses were carried out by using a general linear model (GLM) contrast for task against baseline to identify regions of interest (ROIs), and then examining the activity of these ROIs, either with respect to their correlation with different stimulus parameters, or with respect to their correlation with one another. The goal of the initial step of this process is to identify candidate regions that can be used to test various hypotheses about the reading system. But the use of a general linear model based contrast to identify functionally distinct regions raises a number of difficulties. For example, it is possible to combine functionally distinct regions that happen to be contiguous: because each voxel's time series is only evaluated with respect to its correlation to a model of the task, voxels with very different activity patterns over the course of the experiment are treated in the same way by the thresholding technique. Indeed, the logic of the analysis depends on this to avoid circularity; differences in the correlations among regions are only possible to the extent that their activity is not task-driven in exactly the same way. Further, the standard practice of using a sphere of pre-determined size as the region over which summary statistics are calculated is clearly a problematic simplification: spheres are unlikely to respect functional or anatomical boundaries, so that data from regions defined this way generally include some contribution from multiple, potentially independent sources, including neighboring cortical regions.

Thus, while it is clear that much can be learned by a two-stage approach to data analysis, in which regions of interest are identified in a first stage, and details of their activity profiles explored in a second, the standard approach to identifying regions of interest leaves much to be desired. A relatively novel approach to identifying functionally related regions in fMRI data involves the application of data-driven procedures such as Principal Component Analysis (Hasson, Nir, Levy, Fuhrmann, & Malach, 2004) and Independent Component Analysis (ICA) (Beckmann & Smith, 2004; McKeown et al., 1998). The typical GLM-based approach to fMRI data analysis treats each voxel in the dataset as a separate dependent variable and tests hypotheses about the relationships between their activation over time and a model of the task. Functional regions of interest are then identified by looking for

contiguous sets of voxels that are similar with respect to their fit to the task model. In the ICA approach, spatially independent patterns of activity are identified in the data without reference to the experimental design. This has the effect of isolating potential patterns of activity which are *a priori* functionally distinct in the context of the experiment. It is then possible to examine how these patterns relate to the task while eschewing many of the acknowledged difficulties with model-driven identification of ROIs (e.g., Vul, Harris, Winkelman, & Pashler, 2009). This is accomplished by testing for correlations between a task model and the temporal modes of Independent Components (ICs).

In the current study, we apply this approach to studying functionally distinct regions and networks based on an experiment in which participants perform a one-back task on Chinese characters and “pseudo-characters” that vary with respect to how they encode structured sublexical information, and artificial stimuli that have only surface similarity to real characters. The stimulus design takes advantage of an unusual aspect of the Chinese writing system: single characters contain probabilistic cues to both semantic and phonological information, so that even pseudo-characters can vary with respect to whether they afford phonological and/or semantic interpretations. This differs from alphabetic writing systems, in which it is not possible to have well-formed but unpronounceable strings, nor is it straightforward to have probabilistic cues to meaning in novel strings. By examining correlations between these specific stimulus types and summary time series from regions identified in the ICA, we can determine the functional specificity of the identified regions with respect to these stimulus properties.

The stimuli are designed to test hypotheses about the role of sublexical processing in Chinese. Because of its unusual writing system, a number of theorists have claimed that Chinese reading is “purely lexical,” meaning that mappings from spelling to sound do not involve any sublexical units – this contrasts with alphabetic orthographies, which are thought to permit “assembled” phonology, whereby a pronunciation can be arrived at by the application of rules to sets of letters corresponding to spoken phonemes (Perfetti, Liu, & Tan, 2005). Models that assume a different functional architecture for Chinese (see also Coltheart, Rastle, Perry, Langdon, & Ziegler, 2001) can be contrasted with models of Chinese reading that use essentially the same architecture for Chinese as has been used in alphabetic orthographies (Chen & Peng, 1994; Yang, McCandliss, Shu, & Zevin, 2009). Such models, which assume that individual characters are learned via a statistical mechanism that permits similarity-based generalization, can be shown to make particular use of sublexical units such as phonetic components to create efficient mappings from spelling to sound. In principle, similar effects should be observed in mappings from spelling to meaning, although this has not been directly tested in the models (although Harm & Seidenberg, 2004, were able to find some effects of morphological and quasi-morphological spelling patterns in their model).

Behavioral data are inconclusive with respect to the use of sublexical information in Chinese reading. This is in part because it is difficult to elicit interpretable responses to pseudo-character stimuli. The fact that orthography to phonology mappings are so highly probabilistic makes it such that nonword naming – a staple of studies in alphabetic languages – is not a very natural task for Chinese readers. Thus, studies such as those of Andrews and Scarratt (1998), Treiman, Kessler, and Bick (2003), and Treiman and Kessler (2006) that have been highly influential in establishing that spelling-to-sound statistics from multiple grain sizes are operative in English (see also models of these studies in Zevin & Seidenberg, 2006) cannot be done. By conducting a short-term memory task with stimuli that vary in their sublexical properties, we hope to understand how probabilistic sublexical information contributes to Chinese processing. A strong prediction of the “purely lexical” view would be that gross differences may be observed in the brain networks that support

characters and non-characters, but that sublexical manipulations, particularly within pseudo-characters, should differ little. In contrast, the approach described in Yang, McCandliss, Shu, and Zevin (2008) (see also Yang et al., 2009) suggests that sublexical information should influence brain responses to both real and pseudo-characters, and that such responses should emerge in the same regions responsible for print-to-sound mappings in alphabetic writing systems.

Method

Participants

Eighteen university students (14 female, all right-handed) from Beijing Normal University participated in the study. All were native speakers of Mandarin Chinese with normal or corrected normal vision, aged between 19 and 25, with no history of neurological disease or learning disability. They provided informed written consent approved by the University's internal review board and were paid an hourly stipend.

Materials

Stimuli comprised real Chinese characters, pseudo-characters and “artificial” control characters. The real characters were selected to vary with respect to whether they contained sublexical cues to their pronunciation and meaning. This was possible because many Chinese characters are “phonograms,” comprising a combination of a phonetic component (that provides probabilistic information about pronunciation) with a semantic component (that provides probabilistic information about meaning). To avoid stimulus differences based on familiarity of the visual features, all stimuli were composed of two components with left-right alignment and were matched for the number of radicals and strokes, as shown in Table 1. We also matched how often each component occurs in characters and how often it appears in its modal position (left or right) according to two Chinese corpora: *Tsinghua Balanced Corpus* (Sun, 2006) and *Modern Chinese Frequency Dictionary* (Language & Teaching Institute, 1986). All together, 160 stimuli were used (20 in each of eight conditions).

Three types of characters were constructed: (1) characters containing both Phonetic and Semantic components (PS), (2) characters containing Only Semantic components (OS) and (3) an Only Orthographic (OO) condition, in which neither phonetic nor semantic components were present. Words were matched for properties known to influence reading performance (see Table 1).

Pseudo-characters were constructed in order to permit a parallel manipulation of the availability of phonological and/or semantic information, by recombining semantic and phonological components into configurations that do not correspond to real words. These comprise pseudo-characters with phonological and semantic cues (PS), pseudo-characters with only semantic cues (OS) and pseudo-characters with only orthographic cues (OO).

Artificial control stimuli were constructed by arranging subcomponents of real characters into combinations that are orthotactically illegal (analogous to the use of consonant strings in alphabetic writing systems). Two types of orthotactic violation were used, although they are considered together in the context of the current analysis: the reversed radicals (RR) condition was composed by reversing the position of components in the OO pseudo-characters. The NN condition was composed by randomizing the individual strokes that made up the RR stimuli (see Fig. 1C for examples of all stimulus classes).

Procedure

Participants lay comfortably in the scanner and viewed stimuli via rear projection. A stimulus was presented on each trial, and participants were instructed to respond to repeated stimuli by pressing a button with their right index finger if the stimulus was repeated from the previous trial. Each stimulus was presented for 500 ms at the center of the screen followed by a 2-s response interval (see Fig. 1). Two fonts (Songti and Bold) were pseudorandomly intermixed; participants were instructed to ignore font in making “repeat” responses.

A blocked design was used in which six stimuli of the same type were presented in 15-s blocks, followed by 12.5 s of fixation. The number of repeated stimuli per block was varied from zero to two, so that nearly every stimulus would be potentially task-relevant (if only one target occurred per block, participants could “tune out” after identifying a repeat). In each scanning run, nine fixation blocks and one stimulus block per condition (i.e., eight stimulus blocks) were presented. Eight scanning runs were conducted, requiring 320 stimuli. Because only 160 stimuli were employed, the experiment was designed in halves, with the same stimuli re-cycled in the second half. The task was completed in approximately one half hour.

MRI acquisition

Functional and Anatomical images were collected using a 3T Siemens Magnetom TrioTim Syngo MR system in the State Key Laboratory of Cognitive Neuroscience and Learning of Beijing Normal University in China. Functional images were collected using a gradient-recalled-echo echo-planar imaging (GRE-EPI) sequence sensitive to the BOLD signal. Forty-one axial slices were collected with the following parameters: TR = 2500 ms, TE = 30 ms, flip angle = 90°, FOV = 20 cm, matrix = 64 × 64, and 3 mm interleaved slices with no gap, yielding a voxel size of 3.125 × 3.125 × 3 mm. A total of eight functional runs were collected (93 TRs in each run). Following the acquisition of functional data, high resolution T1-weighted anatomical reference images were obtained using a 3D magnetization prepared rapid acquisition gradient echo (MPRAGE) sequence, TR = 2530 ms, TE = 3.45 ms, flip angle = 7°, FoV = 25.6 cm, matrix = 256 × 256 with 1 mm thick sagittal slices (voxel size of 0.983 × 0.983 × 1 mm).

Data analysis

Functional data were analyzed using AFNI (Cox, 1996, program names appearing in parenthesis below are part of the AFNI suite). Cortical surface models were created with FreeSurfer (available at <http://surfer.nmr.mgh.harvard.edu/>), and functional data projected into anatomical space using SUMA (Saad, Reynolds, Argall, Japee, & Cox, 2004; Argall, Saad, & Beauchamp, 2006, AFNI and SUMA are available at <http://afni.nimh.nih.gov/afni>).

Preprocessing

After reconstructing 3D AFNI datasets from 2D images (to 3D), the anatomical and functional datasets for each participant were co-registered using positioning information from the scanner. The first three volumes were discarded, and functional datasets preprocessed to correct slice timing (3dTshift) and head movements (3dvolreg), reduce extreme values (3dDespike) and detrend linear and quadratic drifts (3dDetrend) from the time series of each run, with no smoothing or filtering. All eight runs were concatenated (3dTcat) and the resulting dataset were then converted to Talairach and Tournoux (1988) space (@auto_t1rc, to the N27 template) at 2 × 2 × 2 mm. An averaged dataset for all 18 participants' times series was computed (3dMean) as the input for the following ICA; across-subject averaging of time-series is computationally efficient and yields results

comparable to more complex methods of treating group data, particularly when hypotheses are focused on ICs that are common across individuals (Schmithorst & Holland, 2004).

Independent component analysis

In order to identify coherent patterns of BOLD response over the course of the experiment, a data-driven approach was applied to the preprocessed time series. This analysis was carried out using Probabilistic ICA (Beckmann & Smith, 2004) as implemented in MELODIC (Multivariate Exploratory Linear Decomposition into Independent Components) Version 3.09, part of FSL (FMRIB's Software Library, www.fmrib.ox.ac.uk/fsl). Averaged preprocessed data for all participants were then whitened and projected into a 90-dimensional subspace using probabilistic Principal Component Analysis where the number of dimensions was estimated using the Laplace approximation to the Bayesian evidence of the model order (Beckmann & Smith, 2004; Minka, 2000). The whitened observations were decomposed into sets of vectors, which describe signal variation across the temporal domain (time-courses) and across the spatial domain (maps) by optimizing for non-Gaussian spatial source distributions using a fixed-point iteration technique (Hyvarinen, 1999). Estimated Component maps were divided by the standard deviation of the residual noise and thresholded ($p > 0.5$) by fitting a Gaussian/Gamma mixture model to the histogram of intensity values (Beckmann & Smith, 2004).

Correlation analysis

The temporal modes of all ICs arrived at by MELODIC were examined for their association with experimental conditions using a correlation approach analogous to the more common general linear model approach to analysis of fMRI data. For each stimulus type, the block design was convolved with a hypothetical hemodynamic response function (waver), and its correlation with each IC's temporal mode was computed. Only ICs significantly correlated ($p < 0.05$) with one of the task-based regressors were considered as the task-related and included for further analysis.

The spatial components observed in ICA can be widely distributed across anatomical regions, making it difficult to compare results of this analysis to the more common region-of-interest based approach. To obtain spatially discrete regions of interest for further analyses, we selected thresholded spatial patterns obtained by MELODIC, using both magnitude ($Z > 3.48$, $p < .0005$, uncorrected) and extent (cluster size > 50 , $2 \times 2 \times 2$ voxels) to achieve a corrected threshold of $p < .005$ (see example in Fig. 3C). Each region was then used as a mask to extract data from the group mean time series (3dmaskave), resulting in a representative time series for each region (Fig. 3D). We then explored the correlation of each region with task models using pairwise correlations. Significant correlations ($p < .05$) are reported in the conjunction analyses in Fig. 4, Tables 3 and 4. Further, where tests between conditions were conducted, these are based on analyses in which the time series from the selected region was extracted from each participant's data and correlated with the task model. Inferential statistics for differences from zero or differences between conditions are based on group t -tests on the normalized regression coefficients (Z statistic) from these analyses.

Results

Behavioral results

As shown in Fig. 2, analysis of the behavioral data from the one-back task revealed a graded effect of familiarity across all eight conditions, which was only marginally significant for response latency, $F_1(7,119) = 1.84$, $MSE = 6916.02$, $p = 0.09$ by subjects, $F_2(7,56) = 1.11$, $MSE = 2502.96$, $p = 0.37$ by items, and significant for accuracy, $F_1(7,119) = 3.73$, $MSE =$

0.03, $p = 0.001$, $F_2(7,56) = 2.08$, $MSE = 0.011$, $p = 0.061$. Real characters produced faster and more accurate responses than pseudo-characters, which in turn were easier to detect as repetitions than the artificial stimuli. When treated as three conditions in this way, the effect of word-likeness was highly reliable for both response latency $F_1(2,34) = 4.26$, $MSE = 9379.08$, $p < 0.05$, $F_2(2,61) = 3.373$, $MSE = 7160.55$, $p < 0.05$ and accuracy $F_1(2,34) = 11.13$, $MSE = 0.03$, $p < 0.01$, $F_2(2,61) = 5.24$, $MSE = 0.03$, $p < 0.01$. Post hoc t -test (Bonferroni corrected) revealed artificial stimuli produced less accurate responses than real ($p < 0.01$) and pseudo-characters ($p < 0.05$), and slower than pseudo ($p < 0.05$) but not real characters. There was a marginal difference between the real and pseudo-characters for accuracy ($p = 0.06$), but not for latency. Thus, familiarity had a strong influence on the participants' ability to detect stimulus repetitions.

Overall results of independent component analysis

Ninety ICs were identified by Melodic ICA analysis. Twenty nine ICs were identified as being significantly correlated ($p < .05$) with predictors for all task blocks combined, or for any of three major classes of stimuli – real characters, pseudo-characters or artificial control stimuli – as shown in Table 2. The remaining components are not discussed in detail but include regions associated with the “default network” (Buckner, Andrews-Hanna, & Schacter, 2008, that are in general negatively correlated with the task vs. rest model) for example. Although the following analyses are based on spatially discrete regions extracted from the ICA, it is clear that many of the components are widely distributed, suggesting intimate functional networks, for example, between occipitotemporal and superior parietal cortices bilaterally, in the context of the task. From the 29 components identified as task relevant, a total of 65 regions of interest were extracted.

Shared and distinct networks for real characters, pseudo-characters and artificial stimuli

As shown in Fig. 4A and Table 3, activity in a network including the bilateral fusiform, inferior frontal gyrus (IFG), middle frontal gyrus (MFG) and superior parietal cortex is correlated with task independent of stimulus type. Thalamus was also highly correlated with all three classes of stimuli. Thus, the shared network across all stimulus classes was largely consistent with results from task vs. rest contrasts in numerous studies of Chinese character recognition (Bolger, Perfetti, & Schneider, 2005; Liu, Dunlap, Fiez, & Perfetti, 2007; Liu et al., 2008; Peng et al., 2004; Tan, Laird, Li, & Fox, 2005).

Few regions appeared to be specifically tuned to real words and more word-like stimuli: only the left temporo-parietal regions was selective for real characters independent of other stimulus types. The lingual gyrus bilaterally and left superior frontal gyrus (SFG) were common to the real and pseudo-character conditions only. In contrast, many more regions were identified as selective to non-word stimuli (i.e., both pseudo-characters and artificial control stimuli) including bilateral visual cortex, a large region of superior and inferior parietal lobule near postcentral gyrus and two small regions within the right middle frontal gyrus. In addition, a number of regions in the right hemisphere, including post-central and superior frontal gyri were selective to the artificial stimuli. One possibility is that the less familiar (and less word-like) stimuli required the recruitment of a more widespread network of brain regions to maintain in short term memory during the one-back task.

Shared and distinct networks for different types of sublexical information

Fig. 4B shows the results of a conjunction analysis for regions whose activity is correlated with Phonological and Semantic (PS), Only Semantic (OS) and Only Orthographic (OO) stimulus classes, irrespective of lexicality. The core “task” network from the previous analyses was again correlated with all three stimulus classes, including portions of fusiform, medial frontal, inferior frontal, middle frontal and superior parietal cortex bilaterally.

Stimuli that contained sublexical semantic information (OS and PS) were selectively associated with large portions of bilateral lingual gyrus, along with thalamus and two small sections of right middle frontal gyrus (BA6/9).

A very large region, comprising most of left post-central gyrus, and another region in left inferior occipital gyrus, in addition to two very small regions in anterior middle temporal gyrus (MTG), SFG and inferior parietal gyrus were selectively activated by stimuli containing only sublexical semantic information (OS). In contrast, only right middle temporal gyrus was selectively activated by stimuli containing both semantic and phonological sublexical information (PS). OS and OO shared two large regions in bilateral superior parietal lobule, precuneus, and a small portion at right middle occipital gyrus.

Comparison of data-driven ROI identification with regions identified by standard task vs. rest GLM contrast

In order to explore the relationship between the current analyses and what could be found with a more typical GLM-based approach, we tested each IC for spatial overlap with a map based on a simple task vs. rest GLM contrast. In this way, we identified seven components that shared more than 50% of their voxels with the task vs. rest contrast; interestingly, the mean overlap of all components that correlated significantly with task vs. rest was 26% (SD = 33%), suggesting that the ICA identified a much larger number of components than were found in the GLM contrast. As shown in Fig. 7, the spatial extent of these components includes activity in ventral temporal, middle frontal, inferior frontal and superior parietal regions found in the task vs. rest contrast. Further, the ICA revealed ICs that are treated as undifferentiated volumes in the task vs. rest contrast, for example dividing the activation that straddles MFG, IFG and precentral gyrus into an inferior/anterior aspect and a superior/posterior aspect.

Fig. 7 also shows the correlations with individual stimulus conditions for regions identified by this technique. The regions of ICs one and two that overlap with the task vs. rest contrast include both regions along the occipitotemporal junction and the superior parietal lobe (SPL). In both cases, activity level increased with task difficulty, such that activity was greatest for the artificial stimuli, least for the real characters and intermediate for the pseudo-characters. This pattern was more pronounced for the SPL than the ventral temporal regions in both cases. The anterior and posterior aspects of MFG identified by ICs four and six also showed a trend to respond most strongly to the most difficult conditions (although in these regions the pseudo-characters patterned with the artificial stimuli) whereas responses in IFG were relatively flat.

Discussion

We identified a large number of ICs that were strongly correlated with the overall task. Further, conjunction analyses suggested that a plurality of these were activated significantly during processing of all stimulus classes. This was true when stimulus class was considered in terms of lexicality (comparing real, pseudo and artificial characters) or in terms of their sublexical structure (comparing stimuli with cues to semantic or phonological information). Overall, activity extent (in terms of the number of regions involved) and level (in terms of strength of correlation with task predictors) was related to task difficulty, particularly in regions such as ventral occipitotemporal, and inferior frontal commonly found in studies of reading across orthographies (e.g., Fiez, Balota, Raichle, & Petersen, 1999; Paulesu et al., 2000) as well as middle frontal gyrus which is particularly important for Chinese reading (Lee et al., 2004; Peng et al., 2004; Tan, Feng, Fox, & Gao, 2001). In contrast, a number of regions were apparently tuned to particular sublexical stimulus properties, including

perisylvian regions, which are implicated in sublexical spelling-to-sound mapping in other languages, but are not typically observed to be active during Chinese reading.

Sensitivity to difficulty in the reading network for Chinese

In large part, patterns of activity identified in the current study were consistent with prior studies of Chinese reading. Both ICA-based and GLM-based analyses revealed task-driven activity in the ventral occipitotemporal (OT), inferior frontal and middle frontal cortices. In addition, robust task-related activity was found in SPL, which is less frequently observed in studies of reading. The inferior frontal and ventral occipitotemporal activations are highly consistent with the literature on reading across orthographies (e.g., Bolger et al., 2005; Tan et al., 2005; Turkeltaub, Eden, Jones, & Zeffiro, 2002). It is not unusual for activity in IFG to be related to task difficulty, as it appears to be here – activity is greatest for the condition in which accuracy is the lowest. More surprisingly, the same pattern was observed in ventral occipitotemporal cortex, which, in many experimental contexts (McCandliss, Cohen, & Dehaene, 2003; Price & Devlin, 2004), responds more strongly to real words or characters than to the artificial stimuli that elicited the strongest responses in this study (see Wang, Yang, Shu, & Zevin, in press, for further discussion of this pattern).

Middle frontal gyrus (MFG) activity is only occasionally observed in studies of alphabetic reading (Sabsevitz, Medler, Seidenberg, & Binder, 2005), but is very strongly associated with Chinese reading (Booth et al., 2006; Tan, Liu, et al., 2001; Tan, Feng, et al., 2001; Siok, Jin, Fletcher, & Tan, 2003; Siok, Perfetti, Jin, & Tan, 2004; Lee et al., 2004), perhaps because of its role in spatial working memory (Liu et al., 2007; Petrides, Alivisatos, Meyer, & Evans, 1993; Siok, Niu, Jin, Perfetti, & Tan, 2008). The spatial arrangement of Chinese characters is more complex than the linear arrangement of letters in alphabetic writing systems, and is therefore thought to depend more on spatial working memory. Strong evidence for this hypothesis comes from neuroimaging studies of Korean *Hangul* recognition (e.g., Yoon, Cho, Chung, & Park, 2005), as characters in that writing system share only their spatial arrangement with Chinese characters. The unusual spatial arrangement of Chinese characters, combined with the complexity of mappings among spelling, sound and meaning may account for a particular profile of dyslexia in Chinese that appears to be related to visuo-spatial processing (Ho, Chan, Chung, Lee, & Tsang, 2007) and is associated with weak MFG activity during reading tasks (Siok et al., 2004, 2008).

The superior parietal lobe (SPL) is less frequently observed in reading studies, although a number of studies of Chinese reading have found task-driven activity in this region. For example, Kuo et al. (2004) found SPL activity in a set of matching tasks, which, notably, was strongest when the stimuli were unfamiliar Korean *Hangul* syllables. They interpret this in terms of top-down processing of spatial information, in line with the characterization of SPL as critical for visuo-spatial attention (Corbetta, Miezin, Shulman, & Petersen, 1993; Corbetta, Shulman, Miezin, & Petersen, 1995); the current data support this hypothesis in part, but the tight relationships between ROIs in SPL and FG are curious in light of the fact that FG is on the ventral stream. Interestingly, Chen, Fu, Iversen, Smith, and Matthews (2002) compared Chinese character reading to pinyin (phonetic spelling of Chinese using Roman letters) and found greater activation during pinyin reading than characters. Thus, it may be that this region is particularly engaged by reading tasks that involve processing relatively unfamiliar stimulus configurations.

Direct comparison of the ICA-based analysis and the GLM contrast between task and rest revealed multiple ICs within the single “blobs” identified in the GLM contrast for MFG, SPL and OT. It is difficult to say anything conclusive about the functional selectivity of the regions identified this way – indeed, they tend to have very similar patterns of correlation across stimulus classes when tested against the block design of the study. One promising

avenue of future research will be to use an event related design with variability across a number of stimulus parameters in order to relate regions that emerge as candidates for being functionally distinct and can be tested for sensitivity to a wide range of stimulus properties (Skipper & Zevin, 2009). For example, stimuli were carefully matched across groups for such features as visual complexity and spatial arrangement, but these and other properties varied within groups – it is possible that some of the components identified as responding similarly across stimulus classes are nonetheless sensitive to these differences.

Sublexical processing in left temporo-parietal and medial occipital cortex

Studies of Chinese reading are often distinguished from reading in alphabetic languages by a marked lack of stimulus-driven activity in left temporo-parietal regions (see meta-analyses in Bolger et al., 2005; Tan et al. (2005)). In alphabetic writing systems, there is some consensus that activity in this region is related to sublexical mapping from orthography to phonology (Pugh et al., 2000). The fact that Chinese readers do not typically activate this region is sometimes taken as evidence that reading Chinese characters does not involve the process of “phonological assembly,” thought to be the function of this region in alphabetic reading (Perfetti et al., 2007; Tan et al., 2005). Indeed, even studies that explicitly tap phonological processing (for example, using rhyme judgment tasks Booth et al., 2006) do not activate this region in Chinese as they do in English.

Stimulus designs that focus on sublexical cues to pronunciation, however, do provide some evidence for processes in this region analogous to print-to-sound conversion in alphabetic orthographies. For example, Lee et al. (2004) found a consistency effect in temporoparietal cortex: characters whose phonetic components were less consistently mapped onto a single pronunciation activated this region more than characters with highly consistent phonetic components. In the current experiment, activity in a large region including temporoparietal cortex, as well as more anterior portions of STG, STS and MTG was found to be selective for real characters that were phonograms (Fig. 5), i.e., they contained both phonological and semantic components. This may be indicative of sublexical print-to-sound mapping for these items.

Some features of the responses in temporo-parietal cortex in the current study are more difficult to explain in terms of sublexical print-to-sound processing, however. Activity in this region was not correlated with the presence of pseudo-character stimuli for which sublexical print-to-sound mappings were available (the PS condition). This contrasts with studies of English, in which similar regions are particularly active to pronounceable nonword stimuli (Booth et al., 2004; Price, 2000; Shaywitz et al., 1998; Tan et al., 2005; Temple et al., 2003; Xu et al., 2001; Xu et al., 2002). Further, the strongest effects in this region were negative correlations with the two artificial stimulus classes.

Another region comprising much of lingual gyrus and middle/inferior occipital gyrus showed evidence of selectivity for sublexical phonological and semantic cues. This can be seen clearly in the medial view of Fig. 4A, in which this region is shown to respond selectively to words and pseudo-characters, and in Fig. 4B, where the same region responds selectively to items containing phonological or semantic components, independent of lexicality. When we examine the correlations of this region across stimulus classes (Fig. 6), it is clear that it is equally correlated with both real characters and pseudo-characters that contain such cues, but not correlated with the presence of stimuli with no such cues. Further, like the temporoparietal region, it is negatively correlated with both classes of artificial stimuli.

Conclusions

A novel approach that included both data-driven search for functional regions and hypothesis-testing for functional specificity of those regions revealed a network whose activity is strongly correlated with recognition of Chinese characters, pseudo-characters and artificial control stimuli. This network was largely consistent with previous studies of Chinese reading, and overlapped substantially with the results of a conventional GLM-based contrast. In addition, this analysis strategy was also able to identify stimulus-specific response patterns that revealed differential sensitivity to different forms of sublexical information not observed before in studies of Chinese reading. In particular, we found some evidence for sublexical print-to-sound processing in temporo-parietal regions, consistent with models that predict a similar functional architecture for Chinese and alphabetic scripts (Yang et al., 2009).

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References

- Andrews S, Scarratt DR. Rule and analogy mechanisms in reading nonwords: Hough dou peapel rede gnew wirds? *Journal of Experimental Psychology: Human Perception and Performance*. 1998; 24(4):1052–1086.
- Argall B, Saad Z, Beauchamp M. Simplified intersubject averaging on the cortical surface using SUMA. *Human Brain Mapping*. 2006; 27:14–27. [PubMed: 16035046]
- Beckmann C, Smith S. Probabilistic independent component analysis for functional magnetic resonance imaging. *IEEE Transactions on Medical Imaging*. 2004; 23(2):137–152. [PubMed: 14964560]
- Bitan T, Booth JR, Choy J, Burman DD, Gitelman DR, Mesulam MM. Shifts of effective connectivity within a language network during rhyming and spelling. *The Journal of Neuroscience*. 2005; 25(22):5397–5403. [PubMed: 15930389]
- Bitan T, Cheon J, Lu D, Burman DD, Booth JR. Developmental increase in top-down and bottom-top processing in a phonological task: An effective connectivity, fMRI study. *Journal of Cognitive Neuroscience*. 2009; 21(6):1135–1145. [PubMed: 18702576]
- Bolger DJ, Perfetti CA, Schneider W. Cross-cultural effect on the brain revisited: Universal structures plus writing system variation. *Human Brain Mapping*. 2005; 25(1):92–104. [PubMed: 15846818]
- Booth JR, Burman DD, Meyer JR, Gitelman DR, Parrish TB, Mesulam MM. Development of brain mechanisms for processing orthographic and phonologic representations. *Journal of Cognitive Neuroscience*. 2004; 16(7):1234–1249. [PubMed: 15453976]
- Booth JR, Lu D, Burman DD, Chou T-L, Jin Z, Peng D-L, et al. Specialization of phonological and semantic processing in Chinese word reading. *Brain Research*. 2006; 1071(1):197–207. [PubMed: 16427033]
- Buckner RL, Andrews-Hanna JR, Schacter DL. The brain's default network: Anatomy, function, and relevance to disease. *Annals of the New York Academy of Sciences*. 2008; 1124:1–38. *The Year in Cognitive Neuroscience 2008*. [PubMed: 18400922]
- Cao F, Bitan T, Booth JR. Effective brain connectivity in children with reading difficulties during phonological processing. *Brain and Language*. 2008; 107(2):91–101. [PubMed: 18226833]
- Chen Y, Fu S, Iversen SD, Smith SM, Matthews PM. Testing for dual brain processing routes in reading: A direct contrast of Chinese character and Pinyin reading using fMRI. *Journal of Cognitive Neuroscience*. 2002; 14(7):1088–1098. [PubMed: 12419131]

- Chen, Y.; Peng, D. A connectionist model of recognition and naming of Chinese characters.. In: Chang, H-W.; Huang, J-T.; Hue, C-W.; Tzeng, O., editors. *Advances in the study of Chinese language processing*. Vol. 1. National Taiwan University Press; 1994. p. 211-240.
- Coltheart M, Rastle K, Perry C, Langdon R, Ziegler J. DRC: A dual route cascaded model of visual word recognition and reading aloud. *Psychological Review*. 2001; 108(1):204–256. [PubMed: 11212628]
- Corbetta M, Miezin FM, Shulman GL, Petersen SE. A PET study of visuospatial attention. *Journal of Neuroscience*. 1993; 13(3):1202–1226. [PubMed: 8441008]
- Corbetta M, Shulman GL, Miezin FM, Petersen SE. Superior parietal cortex activation during spatial attention shifts and visual feature conjunction. *Science*. 1995; 270(5237):802–805. [PubMed: 7481770]
- Cox R. AFNI: Software for analysis and visualization of functional magnetic resonance neuroimages. *Computers and Biomedical Research*. 1996; 29:162–173. [PubMed: 8812068]
- Fiez JA, Balota DA, Raichle ME, Petersen SE. Effects of lexicality, frequency, and spelling-to-sound consistency on the functional anatomy of reading. *Neuron*. 1999; 24(1):205–218. [PubMed: 10677038]
- Frost SJ, Mencl WE, Sandak R, Moore DL, Rueckl JG, Katz L, et al. A functional magnetic resonance imaging study of the tradeoff between semantics and phonology in reading aloud. *Neuroreport*. 2005; 16(6):621–624. [PubMed: 15812320]
- Harm MW, Seidenberg MS. Computing the meanings of words in reading: Cooperative division of labor between visual and phonological processes. *Psychological Review*. 2004; 111(3):662–720. [PubMed: 15250780]
- Hasson U, Nir Y, Levy I, Fuhrmann G, Malach R. Intersubject synchronization of cortical activity during natural vision. *Science*. 2004; 303(5664):1634. [PubMed: 15016991]
- Ho CS, Chan DW, Chung KKH, Lee S-H, Tsang S-M. In search of subtypes of Chinese developmental dyslexia. *Journal of Experimental Child Psychology*. 2007; 97(1):61–83. [PubMed: 17320097]
- Horwitz B, Rumsey J, Donohue B. Functional connectivity of the angular gyrus in normal reading and dyslexia. *Proceedings of the National Academy of Sciences of the United States of America*. 1998; 95(15):8939–8944. [PubMed: 9671783]
- Hyvarinen A. Fast and robust fixed-point algorithms for independent component analysis. *IEEE Transactions on Neural Networks*. 1999; 10(3):626–634. [PubMed: 18252563]
- Jobard G, Crivello F, Tzourio-Mazoyer N. Evaluation of the dual route theory of reading: A metanalysis of 35 neuroimaging studies. *NeuroImage*. 2003; 20:693–712. [PubMed: 14568445]
- Kuo W-J, Yeh T-C, Lee J-R, Chen L-F, Lee P-L, Chen S-S, et al. Orthographic and phonological processing of Chinese characters: An fMRI study. *NeuroImage*. 2004; 21(4):1721–1731. [PubMed: 15050593]
- Language and Teaching Institute of Beijing Linguistic College. *Modern Chinese frequency dictionary*. Beijing Language Institute Publisher; Beijing: 1986. in Chinese
- Lee C-Y, Tsai J-L, Kuo W-J, Yeh T-C, Wu Y-T, Ho L-T, et al. Neuronal correlates of consistency and frequency effects on Chinese character naming: An event-related fMRI study. *NeuroImage*. 2004; 23(4):1235–1245. [PubMed: 15589089]
- Liu Y, Dunlap S, Fiez J, Perfetti C. Evidence for neural accommodation to a writing system following learning. *Human Brain Mapping*. 2007; 28(11):1223–1234. [PubMed: 17274024]
- Liu C, Zhang W-T, Tang Y-Y, Mai X-Q, Chen H-C, Tardif T, et al. The visual word form area: Evidence from an fMRI study of implicit processing of Chinese characters. *NeuroImage*. 2008; 40(3):1350–1361. [PubMed: 18272399]
- McCandliss BD, Cohen L, Dehaene S. visual word form area: Expertise for reading in the fusiform gyrus. *Trends in Cognitive Sciences*. 2003; 7:293–299. [PubMed: 12860187]
- McKeown MJ, Jung T-P, Makeig S, Brown G, Kindermann SS, Lee T-W, et al. Spatially independent activity patterns in functional MRI data during the Stroop color-naming task. *Proceedings of the National Academy of Sciences of the United States of America*. 1998; 95(3):803–810. [PubMed: 9448244]
- Minka, T. Automatic choice of dimensionality for PCA (Tech. Rep.). MIT Media Lab Vision and Modeling Group; 2000. Technical Report 514

- Paulesu E, McCrory E, Fazio F, Menoncello L, Brunswick N, Cappa SF, et al. A cultural effect on brain function. *Nature Neuroscience*. 2000; 3(1):91–96.
- Peng D, Ding G.-s. Perry C, Xu D, Jin Z, Luo Q, et al. fMRI evidence for the automatic phonological activation of briefly presented words. *Cognitive Brain Research*. 2004; 20(2):156–164. [PubMed: 15183388]
- Penny W, Stephan K, Mechelli A, Friston K. Modelling functional integration: A comparison of structural equation and dynamic causal models. *NeuroImage*. 2004; 23:264–274.
- Perfetti CA, Liu Y, Fiez J, Nelson J, Bolger DJ, Tan L-H. Reading in two writing systems: Accommodation and assimilation of the brain's reading network. *Bilingualism: Language and Cognition*. 2007; 10(2):131–146.
- Perfetti CA, Liu Y, Tan LH. The lexical constituency model: Some implications of research on Chinese for general theories of reading. *Psychological Review*. 2005; 112(1):43–59. [PubMed: 15631587]
- Petrides M, Alivisatos B, Meyer E, Evans AC. Functional activation of the human frontal cortex during the performance of verbal working memory tasks. *Proceedings of the National Academy of Sciences*. 1993; 90(3):878–882.
- Price CJ. The anatomy of language: Contributions from functional neuroimaging. *Journal of Anatomy*. 2000; 197:335–359. [PubMed: 11117622]
- Price CJ, Devlin JT. The pro and cons of labelling a left occipitotemporal region: The visual word form area. *NeuroImage*. 2004; 22(1):477–479. [PubMed: 15110041]
- Pugh KR, Mencl WE, Jenner AR, Katz L, Frost SJ, Lee JR, et al. Neurobiological studies of reading and reading disability. *Journal of Communication Disorders*. 2000; 34(6):479–492. [PubMed: 11725860]
- Pugh KR, Mencl W, Shaywitz B, Shaywitz S, Fulbright R, Constable R, et al. The angular gyrus in developmental dyslexia: Task-specific differences in functional connectivity within posterior cortex. *Psychological Science*. 2000; 11(1):51–56. [PubMed: 11228843]
- Rayner K, Foorman B, Perfetti C, Pesetsky D, Seidenberg M. How psychological science informs the teaching of reading. *Psychological Science in the Public Interest*. 2001; 2(2):31–74.
- Saad Z, Reynolds R, Argall B, Japee S, Cox R. SUMA: An interface for surface-based intra- and inter-subject analysis with AFNI. *IEEE International Symposium on Biomedical Imaging: Nano to Macro*. 2004:1510–1513.
- Sabsevitz DS, Medler DA, Seidenberg M, Binder JR. Modulation of the semantic system by word imageability. *NeuroImage*. 2005; 27(1):188–200. [PubMed: 15893940]
- Schmithorst VJ, Holland SK. Comparison of three methods for generating group statistical inferences from independent component analysis of functional magnetic resonance imaging data. *Journal of Magnetic Resonance Imaging*. 2004; 19(3):365–368. [PubMed: 14994306]
- Seidenberg MS, McClelland JL. A distributed, developmental model of word recognition and naming. *Psychological Review*. 1989; 96(4):523–568. [PubMed: 2798649]
- Shaywitz SE, Shaywitz BA, Pugh KR, Fulbright RK, Constable RT, Mencl WE, et al. Functional disruption in the organization of the brain for reading in dyslexia. *Proceedings of the National Academy of Sciences*. 1998; 95(5):2636–2641.
- Siok WT, Jin Z, Fletcher P, Tan LH. Distinct brain regions associated with syllable and phoneme. *Human Brain Mapping*. 2003; 18(3):201–207. [PubMed: 12599278]
- Siok WT, Niu Z, Jin Z, Perfetti CA, Tan LH. A structural–functional basis for dyslexia in the cortex of Chinese readers. *Proceedings of the National Academy of Sciences*. 2008; 105(14):5561–5566.
- Siok WT, Perfetti CA, Jin Z, Tan L. Biological abnormality of impaired reading is constrained by culture. *Nature*. 2004; 431(7004):71–76. [PubMed: 15343334]
- Skipper, JI.; Zevin, JD. The neurobiology of communication in natural settings.. Poster presented at the Neurobiology of language conference (NLC2009); Chicago, IL, USA. 2009.
- Skipper JI, Goldin-Meadow S, Nusbaum HC, Small SL. Gestures orchestrate brain networks for language understanding. *Current Biology*. 2009; 19(8):661–667. [PubMed: 19327997]
- Sun, M. Balanced corpus of modern Chinese. Tsinghua University AI and NLP Group; 2006. in Chinese

- Talairach, J.; Tournoux, P. Co-planar stereotaxic atlas of the human brain. Thieme Medical Publishers, Inc.; New York: 1988.
- Tan LH, Feng CM, Fox PT, Gao JH. An fMRI study with written Chinese. *Neuroreport*. 2001; 12(1): 83–88. [PubMed: 11201097]
- Tan LH, Liu H-L, Perfetti CA, Spinks JA, Fox PT, Gao J-H. The neural system underlying Chinese logograph reading. *NeuroImage*. 2001; 13(5):836–846. [PubMed: 11304080]
- Tan LH, Laird AR, Li K, Fox PT. Neuroanatomical correlates of phonological processing of Chinese characters and alphabetic words: A meta-analysis. *Human Brain Mapping*. 2005; 25(1):83–91. [PubMed: 15846817]
- Temple E, Deutsch GK, Poldrack RA, Miller SL, Tallal P, Merzenich MM, et al. Neural deficits in children with dyslexia ameliorated by behavioral remediation: Evidence from functional MRI. *Proceedings of the National Academy of Sciences, USA*. 2003; 100(5):2860–2865.
- Treiman R, Kessler B. Spelling as statistical learning: Using consonantal context to spell vowels. *Journal of Educational Psychology*. 2006; 98(3):642–652.
- Treiman R, Kessler B, Bick S. Influence of consonantal context on the pronunciation of vowels: A comparison of human readers and computational models. *Cognition*. 2003; 88(1):49–78. [PubMed: 12711153]
- Turkeltaub PE, Eden GF, Jones KM, Zeffiro TA. Meta-analysis of the functional neuroanatomy of single-word reading: Method and validation. *NeuroImage*. 2002; 16(3, Part 1):765–780. [PubMed: 12169260]
- Vul E, Harris C, Winkielman P, Pashler H. Puzzlingly high correlations in fMRI studies of emotion, personality, and social cognition. *Perspectives on Psychological Science*. 2009; 4(3):274–290.
- Wang X, Yang J, Shu H, Zevin JD. Left fusiform BOLD responses are inversely related to word-likeness in a one-back task. *NeuroImage*. in press.
- Xu B, Grafman J, Gaillard WD, Ishii K, Vega-Bermudez F, Pietrini P, et al. Conjoint and extended neural networks for the computation of speech codes: The neural basis of selective impairment in reading words and pseudowords. *Cerebral Cortex*. 2001; 11(3):267–277. [PubMed: 11230098]
- Xu B, Grafman J, Gaillard WD, Spanaki M, Ishii K, Balsamo L, et al. Neuroimaging reveals automatic speech coding during perception of written word meaning. *NeuroImage*. 2002; 17(2):859–870. [PubMed: 12377160]
- Yang, J.; McCandliss, BD.; Shu, H.; Zevin, JD. Division of labor between semantics and phonology in normal and disordered reading development across languages.. In: Love, B.; McRae, K.; Sloutsky, V., editors. *Proceedings of the 30th annual conference of the cognitive science society*; Washington, DC, USA. Austin, TX: Cognitive Science Society; 2008. p. 445-450.
- Yang J, McCandliss BD, Shu H, Zevin JD. Simulating language-specific and language-general effects in a statistical learning model of Chinese reading. *Journal of Memory and Language*. 2009; 61(2): 238–257. [PubMed: 20161189]
- Yoon HW, Cho K-D, Chung J-Y, Park H. Neural mechanisms of Korean word reading: A functional magnetic resonance imaging study. *Neuroscience Letters*. 2005; 373(3):206–211. [PubMed: 15619544]
- Zevin JD, Seidenberg MS. Simulating consistency effects and individual differences in nonword naming: A comparison of current models. *Journal of Memory and Language*. 2006; 54(2):145–160.

Fig. 1.

Procedure of the experiment. (A) Stimuli were presented in blocks of 15 s interspersed with 12.5 s fixation intervals. (B) In each block, six stimuli were presented for 500 ms with a 2 s inter-trial interval during which the screen was blank. (C) Examples of each stimulus class; stimuli were presented in two fonts – *bold* (left) and *songti* (right) – in order to discourage matching based on low-level visual properties. Note that the left portion of the PS and OS stimuli match; these are semantic components (referring to “cloth” in the real character and “metal” in the pseudo-character). For the PS stimuli, the right portions match, this is a phonetic component, corresponding most often to the syllable /ren/. Note that the OO stimuli also has a left-right organization, but neither of these components has a canonical semantic or phonological mapping. These stimuli were reversed in left-right order to create the RR condition, and their stroke order scrambled to create the NN condition.

Fig. 2.

Behavioral results from the oneback task. Response latency and accuracy are plotted for all eight stimulus conditions (left) and for conditions grouped by stimulus familiarity (right): responses are slowest and least accurate for the artificial stimuli, indicating that detecting repeated stimuli was more difficult for those stimuli.

Fig. 3.

An example of an independent component, and procedures for identifying discrete ROIs: (A) spatial representation of the 4th IC; (B) the temporal mode of the IC, plotted against a model hemodynamic response function (HRF) for the task; (C) separate ROIs identified by applying voxel-wise significance and cluster-size thresholds to the data in (A); (D) time series for each ROI plotted against the model HRF for task vs. rest. Note that these differ slightly from one another, and from the temporal mode of the IC itself.

Fig. 4. Stimulus specificity determined by conjunction analysis of correlations with different stimulus classes. (A) Real characters, pseudo-characters and artificial stimuli; (B) conjunction analysis for characters and pseudo-characters containing phonological and semantic (PS), only semantic (OS) and only orthographic (OO) sublexical structure.

Fig. 5. Stimulus specificity in middle temporal gyrus, superior temporal sulcus and temporo-parietal cortex, bilaterally. (A) Spatial extent of contiguous regions identified as having the same functional specialization via correlation with different stimulus classes; the left temporo-parietal region was selective to only real characters with both phonological and semantic information. (B) Correlation Z-values for each condition; these regions in both hemispheres are selective for real characters with both phonological and semantic sublexical information; selectivity for words over pseudo-words is also observed in the left hemisphere.

Fig. 6. Stimulus specificity in medial extrastriate cortex, including lingual gyrus and middle/inferior occipital gyrus. (A) Spatial extent of contiguous regions identified as having the same functional specialization via correlation with stimulus classes. (B) Correlation Z-values for each condition, revealing positive correlation with the presences of either phonological or semantic information in either words or nonwords, and a negative correlation with items that lack orthographic structure. (C) Time series of % signal change for this region plotted against the model HRF for the artificial (RR and NN) stimulus classes; activity does appear to decrease during blocks containing these stimulus classes, indicating that the negative correlation is not simply a baseline effect relative to conditions that reliably activate the region.

Fig. 7.

Direct comparison of ICA-derived regions of interest with a task vs. rest GLM contrast, shown as a heat map, with overlapping ROIs based on the ICA analysis shown as color-coded outlines. Bar graphs show responses to different stimulus classes in each ROI. * $p < .05$, ** $p < .005$, *** $p < .001$.

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Table 1

Stimulus properties for all conditions.

Condition	n	Radical	Stroke	Sum frequency		Position frequency	
				Corpus	Dictionary	Corpus	Dictionary
<i>Real character</i>							
PS	20	2.85	9.10	8215.93	8047.11	7224.78	7173.61
OS	20	3.00	9.75	7909.58	7841.14	7516.77	7512.50
OO	20	2.70	8.40	8635.49	8544.36	6527.50	6481.22
<i>Pseudo-character</i>							
PS	20	2.85	9.10	8215.93	8047.11	7224.78	7173.61
OS	20	2.80	8.75	7736.44	7630.31	7316.99	7320.00
OO	20	2.75	8.60	8062.85	7841.92	6194.43	6081.78
<i>Artificial</i>							
RR	20	2.75	8.60	8062.85	7841.92	0	0
NN	20	0	8.60	0	0	0	0

Note: n, the number of items; radical, the number of radicals; stroke, the number of strokes; sum frequency, total token frequency of characters that include one or more of the same radicals as the item in the *Modern Chinese Frequency Dictionary* (Language & Teaching Institute, 1986) and *Tsinghua Balanced Corpus* (Sun, 2006); position frequency, total token frequency of characters sharing one or more radical in the same position.

Table 2

Independent components correlated with task ($p < .05$).

IC#	Regions	%EV	r-Value			
			All	Real	Pseudo	Artificial
1	Fusiform gyrus (b), SPL (b)	3.36	30.53	6.23	10.29	11.15
2	IPL (b), SPL (b), MOG (l)	2.80	28.21	2.74	8.89	17.36
4	Medial FG (b), insula (b), precentral (l)	1.95	25.60	8.43	8.49	7.73
6	IFG (b)	1.81	24.90	5.57	8.00	11.52
9	MFG (r), IPL (r)	1.63	17.28	2.70	5.48	12.37
15	IFG (b)	1.37	14.31	3.77	4.62	8.68
7	Precuneus (b), MOG (r)	1.78	12.34	-	4.93	18.01
30	MFG (l)	1.11	11.46	5.93	4.41	3.12
16	IFG (l), postcentral (r)	1.32	10.48	-	3.54	9.92
42	Precentral (b)	0.96	10.26	3.47	6.19	2.55
48	Thalamus (b); hippocampus (b)	0.91	9.81	3.76	3.47	4.79
50	Precentral gyrus (b)	0.91	8.46	2.08	3.87	4.62
17	Lingual gyrus (b)	1.30	8.01	7.52	5.03	-
53	SFG (b)	0.89	7.55	-	2.67	7.17
61	Postcentral (l)	0.88	5.94	4.24	3.66	-
64	Precentral (r)	0.87	5.74	2.69	2.49	-
37	Anterior cingulate	1.60	5.09	-	3.10	-
66	MFG (r), SMG (r)	0.86	4.24	-	-	2.08
23	Insula (b)	1.19	2.23	3.67	-	-
11	Insula (l), postcentral (l) MFG (b)	1.45	2.21	2.99	-	-
46	MTG (r)	0.92	2.14	-	-	4.50
44	SFG (b)	0.94	2.12	-	-	-
89	MTG (r)	0.81	2.11	-	-	-
26	STG (l)	1.15	1.99	1.98	-	-
5	Lingual gyrus (l); IOG (r)	1.82	-	-	-	5.31
28	MTG (b)	1.13	-	6.02	-	-
39	Precuneus (l)	1.00	-	-	-	5.09
58	Fusiform (l)	0.89	-	-	-	3.93

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IC#	Regions	%EV	t-Value		
			All	Real	Pseudo Artificial
71	Middle cingulate gyrus	0.85	-	-	- 2.17

Note: IC#, independent component number; out of 90 components ranked by proportion variance explained; Regions, anatomical regions identified as highly correlated with the IC, %EV, percent of explained variance accounted for, t-value for correlation with each condition, nonsignificant correlations indicated with “-”. SPL = superior parietal lobe; IPL = inferior parietal lobe; MOG = middle occipital gyrus; FG = frontal gyrus; MFG = middle frontal gyrus; IFG = inferior frontal gyrus; SFG = superior frontal gyrus; SMG = supramarginal gyrus; MTG = middle temporal gyrus; l = left; r = right; b = both hemispheres.

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Table 3

Stimulus specificity for functional regions identified by ICA: real characters, pseudo-characters and artificial stimuli.

Region	H	BA	Voxels	Coordinates		
				x	y	z
Real + Pseudo + Artificial						
MFG	L	9	1442	-44	16	27
IFG	L	45	626	-32	25	3
PrG	L	6	180	-24	-12	49
SPL	L	7	927	-27	-65	35
FuG	L	37	1105	-42	-57	-12
MeFG	B	6	1150	4	2	53
MFG	R	9	485	40	7	33
IFG	R	45	814	37	25	4
PrG	R	6	153	38	-8	49
SPL	R	7	78	26	-59	44
IPL	R	40	69	40	-42	39
FuG	R	37	710	42	-54	-15
Th	B		228	0	-11	12
Real + Pseudo						
SFG	L	6	320	-15	-13	66
LgG	B	18	2290	1	-81	6
Pseudo + Artificial						
PrG	L	6	63	-22	-13	49
IPL	L	40	1685	-34	-48	44
IOG	L	18	1073	-27	-82	-5
MFG	R	9	192	40	29	35
MFG	R	6	122	32	4	56
SPL	R	7	2294	31	-61	43
MOG	R	19	106	47	-54	-6
IOG	R	18	987	30	-82	-5
Real						
MTG	L	22	983	-54	-34	5

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Region	H	BA	Voxels	Coordinates		
				x	y	z
<i>Artificial</i>						
SFG	R	8	259	1	29	46
MFG	R	46	80	40	44	9
PrG	R	6	56	24	-14	50
PoG	R	2	542	53	-24	33

Note: H = hemisphere, left (L), right (R) or bilateral (B); BA = Brodmann's area; volume is given in number of voxels ($2 \times 2 \times 2$ mm); coordinates (x, y and z) for the central active voxel in each cluster are given with reference to the Talairach atlas; MFG, Middle Frontal Gyrus; PrG, Precentral Gyrus; SPL, Superior Parietal Lobule; FuG, Fusiform Gyrus; MeFG, Medial Frontal Gyrus; IPL, Inferior Parietal Lobule; Tha, Thalamus, SFG, Superior Frontal Gyrus; LiG, Lingual Gyurs; IOG, Inferior Occipital Gyrus; MOG, Middle Occipital Gyrus; MTG, Middle Temporal Gyrus; PoG, Postcentral Gyrus.

Table 4

Stimulus specificity for functional regions identified by ICA: phonological, semantic and orthographic.

Region	H	BA	Volume	Coordinates		
				x	y	z
PS + OS + OO						
MeFG	B	6	1060	-4	1	53
MFG	L	9	1442	-44	16	27
IFG	L	45	626	-32	25	3
PrG	L	6	193	-24	-12	49
SPL	L	7	381	-29	-56	41
FuG	L	37	1105	-42	-57	-12
MFG	R	9	485	40	7	33
IFG	R	45	814	37	25	4
PrG	R	6	153	38	-8	49
SPL	R	7	78	26	-59	44
IPL	R	40	69	40	-42	39
FuG	R	37	710	42	-54	-15
PS + OS						
MFG	R	9	192	40	29	35
MFG	R	6	122	32	4	56
LgG	B	18	2290	1	-81	6
Th	B		228	0	-11	12
OS + OO						
SPL	L	7	1499	-23	-67	44
SPL	R	7	1480	24	-67	43
MOG	R	19	106	47	-54	-6
PS						
MTG	R	22	601	52	-34	4
OS						
PoG	L	2	2162	-42	-26	47
IOG	L	18	904	-27	-85	-4
MTG	R	38	85	30	4	-36

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Region	H	BA	Volume	Coordinates		
				x	y	z
SFG	R	6	413	10	-6	64
IPL	R	40	939	43	-52	43

Note: H = hemisphere, left (L), right (R) or bilateral (B); BA = Brodmann's area; volume is given in number of voxels ($2 \times 2 \times 2$ mm); coordinates (x, y and z) for the central active voxel in each cluster are given with reference to the Talairach atlas. MFG, Middle Frontal Gyrus; IFG, Inferior Frontal Gyrus; PrG, Precentral Gyrus; SPL, Superior Parietal Lobule; FuG, Fusiform Gyrus; MeFG, Medial Frontal Gyrus; IPL, Inferior Parietal Lobule; Th, Thalamus. SFG, Superior Frontal Gyrus; LG, Lingual Gyurs; IOG, Inferior Occipital Gyrus; MOG, Middle Occipital Gyrus; MTG, Middle Temporal Gyrus; PoG, Postcentral Gyrus.