Visual field differences in visual word recognition can emerge purely from perceptual learning: Evidence from modeling Chinese character pronunciation

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Abstract

In Chinese orthography, a dominant character structure exists in which a semantic radical appears on the left and a phonetic radical on the right (SP characters); a minority opposite arrangement also exists (PS characters). As the number of phonetic radical types is much greater than semantic radical types, in SP characters the information is skewed to the right, whereas in PS characters it is skewed to the left. Through training a computational model for SP and PS character recognition that takes into account of the locations in which the characters appear in the visual field during learning, but does not assume any fundamental hemispheric processing difference, we show that visual field differences can emerge as a consequence of the fundamental structural differences in information between SP and PS characters, as opposed to the fundamental processing differences between the two hemispheres. This modeling result is also consistent with behavioral naming performance. This work provides strong evidence that perceptual learning, i.e., the information structure of word stimuli to which the readers have long been exposed, is one of the factors that accounts for hemispheric asymmetry effects in visual word recognition.

Keywords: Computational modeling, Hemispheric asymmetry, visual word recognition, Chinese character recognition, perceptual learning.

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Introduction

Visual field differences in visual word recognition have been consistently reported. For instance, there is a classical right visual field (RVF) advantage in reading English words, demonstrated first in tachistoscopic recognition (e.g., Bryden & Rainey, 1963) and subsequently in other word recognition tasks, including lexical decision (Faust, Babkoff, & Kravetz, 1995), and word naming tasks (Brysbaert & d'Ydewalle, 1990). This RVF advantage has been argued to be linked to the superiority of the left hemisphere (LH) in language processing and shown to interact with sex and handedness (e.g., Voyer, 1996; Kim, 1994).

In addition to this hemispheric dominance account of the RVF advantage, alternative explanations have also been proposed. Mondor and Bryden (1992) proposed an attentional advantage model, which suggests that in addition to a direct access to the LH, this RVF advantage can also be influenced by the distribution of attention; the LH is able to process verbal stimuli with fewer attentional resources allocated, compared with the right hemisphere (RH), and hence gives rise to this RVF advantage. Evidence supporting this model comes from several cueing experiments, showing that verbal stimuli presented to the left visual field (LVF) had stronger cueing effects than those presented to the RVF, because they required more attentional resources (e.g., Nicholls, Wood, & Hayes, 2001).

In Chinese character recognition, in contrast to English, a LVF advantage has been reported in tachistoscopic recognition; this phenomenon has been argued to reflect the RH superiority in handling holistic pattern recognition tasks (Tzeng, Hung, Cotton, & Wang, 1979; note however that a recent study showed a reduced holistic processing effect in Chinese character recognition in Chinese readers compared with non-Chinese readers; Hsiao & Cottrell, 2009), or a more efficient lexical interpretation of character stimuli in the RH, given that no laterality effect was found for pseudo- and non-characters (Cheng & Yang, 1989). As for phonological processing in Chinese character recognition, Weekes and Zhang (1999) reported phonological priming effects on phonetic compound recognition when characters were presented in the RVF but not LVF. Yang and Cheng (1999) also showed that, in a character recognition task, when the orthographic similarity of two alternative items for choice was manipulated, there was a LVF advantage; in contrast, when the phonological similarity of two alternative items for choice was manipulated, there was a RVF advantage. In short, previous divided visual field studies of Chinese character recognition usually exhibited a LVF advantage for orthographic processing and a RVF advantage for phonological processing.

Do these behavioral differences observed in visual hemifield studies always imply fundamental processing differences between the hemispheres? Is it possible that visual field differences can emerge without assuming fundamental processing differences between the two hemispheres? Here we examine the possibility that visual field differences in visual word recognition can emerge purely from perceptual learning, or more specifically, the information structure of the word stimuli to which the readers have long been exposed. We first conduct a computational modeling of visual word recognition, since modeling allows perfect control over variables such as information structures of input word stimuli and fundamental processing differences between the two hemispheres; the model also takes into account the locations in which the characters appear in the visual field during learning. . In order to examine the effect of perceptual learning, in the model we do not assume any fundamental processing difference between the two hemispheres, so that any visual field difference observed in the model is mainly due to information structures of input word stimuli. We then examine the modeling predictions through a corresponding behavioral experiment. The materials used are a major type of Chinese characters, *phonetic compounds*, in order to utilize their distinct information structure in this examination. This type of Chinese characters comprises about 81% of the 7,000 frequent characters in a Chinese dictionary (Li & Kang, 1993). We introduce the structures of these Chinese characters below.

A Chinese phonetic compound consists of a semantic radical, which signifies the meaning of the character, and a phonetic radical, which typically contains partial information about the character pronunciation. For current purposes, we refer to a character whose pronunciation is the same as its phonetic radical as a regular character; characters whose pronunciations are the same as their phonetic radical but with a different tone are semiregular characters; and those whose pronunciations are different from their phonetic radicals are irregular characters. In Chinese phonetic compound recognition, a regularity effect has been reported: regular characters are named faster than irregular characters (e.g., Hue, 1992). Most of the phonetic compounds have a left-right structure; about 90% of them have their semantic radical on the left and the phonetic radical on the right. These characters are referred to as SP characters. The other 10% have the opposite arrangement, with the phonetic radical on the left and the semantic radical on the right, termed PS characters (Hsiao & Shillcock, 2006; Figure 1). Also, in Chinese orthography, the phonetic radical types are much more numerous than the semantic radical types; the ratio is about ten to one (Harbaugh, 1998). In other words, there is greater variability in the phonetic radical.

Hence, in SP characters, the information is skewed to the right, whereas in PS characters, the information is skewed to the left. Given the dominant percentage of SP characters compared with PS characters in the lexicon, the overall information distribution is skewed to the right. As we will show later, the distinction between the structures of SP and PS characters and the overall information skew allow us to demonstrate how visual field differences in visual character recognition can emerge purely from perceptual learning.

We first conduct a computational examination with a computational model of Chinese character recognition (Hsiao & Shillcock, 2004; 2005a; cf. Shillcock & Monaghan, 2001). The model takes into account the locations in which the characters appeared in the visual field during learning (i.e., where the reader makes their eye fixations during learning to read; Figure 2(a)). Since the purpose of the study was to examine the influence of perceptual learning, i.e., whether the information structure of the word stimuli presented in the visual field during learning influences visual word processing in the two visual hemifields, in the model we did not assume any fundamental hemispheric processing differences (such as differential frequency biases proposed in the Double Filtering by Frequency theory, Ivry & Robertson, 1998; see also Hsiao, Shieh, & Cottrell, 2008; or the coarse- and fine-semantic-coding difference between the two hemispheres, Jung-Beeman, 2005) or anatomical specifics in the visual pathways (e.g., whether foveal representation is split and contralaterally projected or whether the information is processed in one or two hemispheres; see Shillcock & Monaghan, 2001; Hsiao & Shillcock, 2005a); instead, we used a typical two-layer neural network with one hidden layer between the input and the output layer (Figure 2(a); it has been referred to as a non-split model in Shillcock & Monaghan, 2001). We show that in a model that does not assume fundamental hemispheric processing asymmetry or splitting architecture, visual field differences emerge as a consequence of the information structure of the materials with which the network is trained. We then show that human behavior is well predicted by such modeling, suggesting the influence of perceptual learning on the observed visual field difference.

Computational Modeling

Figure 2(a) shows our model of Chinese character recognition (i.e. the non-split model in Hsiao & Shillcock, 2005a), which maps an orthographic representation, defined by basic stroke patterns in Chinese orthography, to a corresponding feature-based phonological representation. The input layer is divided with respect to a fixation point in order to simulate different fixation behavior during learning to read; the word input then is projected to a single hidden layer before it reaches the phonological representation in the output layer.

In this model, the input layer representation can be considered as reflecting the results of possible neural computation and information extraction processes from the primary visual cortex up to the lateral occipital region (McCandliss, Cohen, & Dehaene, 2003; cf. Hsiao et al., 2008); the hidden layer can be considered as the Visual Word Form Area (VWFA), a structure within the left fusiform gyrus that has been shown to be particularly responsive to visual words and argued to be a perceptual expertise area for visual word recognition (McCandliss et al., 2003; cf. Hsiao et al., 2008); the phonological representation in the output layer can be considered as the temporal regions anterior to the VWFA that is responsible for phonological processes involved in visual word recognition (McCandliss et al., 2003). Thus, the current model follows the general principles governing visual recognition in the human visual system. Since the model architecture is completely symmetric, any visual field asymmetry effect observed after training can only be due to asymmetry in the information structure of the stimuli presented to the model during training.

Phonological Representation

In the modeling, we adopted a distributed, feature-based phonological representation. The sound system of Chinese differs from that of English. One of the most salient differences is the four distinct tones in standard Chinese (i.e. Mandarin). The pronunciation of each character has only one syllable, which can be divided into three segments: the initial consonant, the nucleus vowel, and the final consonant. Each character also has a tone associated. We encoded the initial consonant in terms of 14 features (i.e., 14 nodes, with each corresponding to a feature): bilabial, labiodental, dental, alveolar, palatal, velar, stop-aspirated, stop-unaspirated, nasal, fricative, affricative-aspirated, affricative-unaspirated, glide, and liquid. Vowels were encoded with 8 features (i.e., 8 nodes): front, central, back, high, mid, low, unround, and round. After 8 vowel feature nodes, we used 3 nodes to represent the features of the consonant in the ending position (nasal, dental, and velar), since there are only two consonants (n and ng) possible in the final position (Wang, 1973). The last 2 nodes represented high and low tones respectively. Four different tones in Chinese were represented with different combinations of the high and low tones (Yip, 2002). In total, the distributed phonological representation consisted of 27 nodes.

Orthographic Representation

Chinese characters consist of several individual strokes. There are some 20+ distinct strokes in Chinese orthography. Together, a few strokes may comprise a "stroke pattern", a recurrent orthographic unit of characters. Some stroke patterns can be characters by themselves. Units can be constructed recursively to form another composite unit. Those units that are integral stroke patterns and cannot be further decomposed into other units have been referred to as *single bodies* (Chen, Allport, & Marshall, 1996). Researchers have long believed that Chinese character recognition starts from an analysis of features and the number of individual strokes (e.g., Seidenberg, 1985), in contrast with letters in alphabetic writing systems. It has recently been shown that this recognition by skilled readers is based upon well-defined orthographic constituents, instead of individual strokes (Chen et al, 1996; Zhou & Marslen-Wilson, 1999). Hence, in the orthographic representation, we used the basic stroke patterns defined in Cangjie, a Chinese transcription system developed by Ban-fu Chu in 1978. From a database analysis, there are 179 such stroke patterns comprising the radicals of all left-right structured Chinese phonetic compounds (Hsiao & Shillcock, 2006). Hence, we used these 179 stroke patterns to encode the orthographic representation of the Chinese characters whose pronunciation we modeled.

Training & Test Corpora

The training corpus contained all left-right structured Chinese phonetic compounds and their radicals that can also be stand-alone characters. During training, each character was presented according to its log token frequency[1], taken from a Chinese lexical database (Hsiao & Shillcock, 2006). The database contains about 3,000 of the most frequent Chinese phonetic compound characters. Among them there are 2,159 left-right structured phonetic compounds and 880 radicals that are also existing characters. The test corpus contained the same phonetic compounds, but not the radicals on their own.

Training & Testing

During the simulation, eye fixation behavior was idealized into three different fixation positions, as shown in Figure 2(b). In order to accommodate such representations, the input layer contained four blocks. When a character was presented in position 1, the current fixation was to the right of the character; in position 2, the fixation was between the two radicals; in position 3, the fixation was to the left of the character. Thus, each block in Figure 2(a) contained 179 nodes, corresponding to the 179 possible stroke patterns. This orthographic input was mapped onto a feature-based phonological output (27 nodes), where the most frequent pronunciation of the input character was presented. The hidden layer contained 100 nodes. During training, each character was presented according to its log token frequency, and equally distributed among the fixation positions. This equal presentation frequency among the fixation positions reflects the finding that there is no tendency for the eyes to land more frequently at a particular position in a character during Chinese text reading (e.g., Tsai & McConkie, 2003)[2]. The learning algorithm was discrete back propagation through time (Rumelhart, Hinton, and Williams, 1986). The learning rate was 0.02. We trained the network with 2,159 of the most frequent left-right structured phonetic compounds, taken from Hsiao & Shillcock (2006), together with their phonetic radicals that can also be stand-alone characters (presented in block 2 and 3 only), and examined its behavior in different fixation positions (see also Hsiao & Shillcock, 2004; 2005a)[3]. The model was trained through approximately 2,471,100 training events; the learning curve was smooth and became steady after approximately 1,647,400 events. The simulation was implemented with PDP++ neural network simulation software (O'Reilly & Munakata, 2000).

Results

The model was run ten times and its average performance over the ten times was analyzed with ANOVA. The independent variables were fixation position (position 1, 2, and 3), character regularity (regular/semiregular vs. irregular), character frequency (high vs. low), and position of the phonetic radical (SP vs. PS). The dependent variable was averaged summed squared error.

The results showed a main effect of fixation position ($F(2, 4302) = 34.301$, $p << 0.001$ with the Greenhouse-Geisser correction[4]), with the best performance in fixation position 1 (Figure 3(a)). This phenomenon can be explained by the overall rightward information skew in the lexicon. This information skew was reflected in the analysis of variability (or entropy in information theory, a measure of the amount of information required to describe a random variable; see Cover & Thomas, 2006) of input stroke patterns received in the four input block during training; as shown in Figure 3(b), block 2, 3, and 4 had a heavier processing demand than block 1 due to the greater variability (cf. Shillcock, Ellison, & Monaghan, 2000). Consequently, the model had the best performance when characters were presented in fixation position 1, *i.e.*, when the character was presented in the LVF. When examining only fixation position 1 and fixation position 3 conditions (i.e., LVF and RVF conditions), the main effect of fixation position was significant ($F(1, 2151) = 19.304$, $p << 0.001$). This result is consistent with the literature showing a LVF advantage in the tachistoscopic recognition of Chinese characters (Which depends mainly on orthographic processing; e.g., Tzeng et al., 1979).

Also, there was a significant three-way interaction between fixation position, character regularity, and position of the phonetic radical ($F(2, 4302) = 16.137$, $p << 0.001$ with the Greenhouse-Geisser correction). When we examined the model's performance in different fixation positions separately, the interaction between character regularity and position of the phonetic radical was the strongest in fixation position 1 ($F(1, 2151) = 13.870$, $p < 0.001$) and the weakest in fixation position 3 ($F < 1$, *n.s.*; see Figure 3(c); when examining only the fixation position 1 and 3, this three-way interaction was also significant, $F(1, 2151) = 23.914$, $p << 0.001$). This phenomenon can be explained by a denser mapping problem presented to the model when characters were presented in fixation position 3 than in fixation position 1 (Figure 3(b)). When PS characters were presented in fixation position 1, the model faced a sparser mapping problem since the phonologically important part of the characters (i.e., the phonetic radical) was presented in block 1, which had the lowest level of entropy; consequently, the model had adequate processing resources to remember individual orthography-to-phonology mappings without generalization. Hence, no regularity effect was observed when PS characters were presented in fixation position 1 (t-test, n.s.; Figure 3(c))[5]; in contrast, when PS characters were presented in fixation position 3, the denser mapping problem, compared with fixation position 1, demanded more generalization in the network. Hence, the regularity effect became significant when PS characters were presented in fixation position 3 ($t(213.627) = -3.481$, $p = 0.001$; Figure 3(c); also in fixation position 2, $t(215) = -2.207$, $p < 0.05$). Indeed, when comparing PS characters' performance in fixation position 1 and 3, there was a significant interaction between fixation position and regularity effect: a stronger regularity effect in fixation position 3 compared with fixation position 1 ($F(1, 1938) = 30.625$, $p < 0.001$; Figure 3(c)).

In contrast, when an SP character was presented in fixation position 3, compared with fixation position 1 and 2, its phonetic radical fell in a block with a lower entropy level (Figure 3(b)); thus, SP characters had a stronger regularity effect in fixation position 1 and 2 compared with fixation position 3 (Position 1, $t(1454.140) = -11.927$, $p < 0.001$; position 2, $t(1561.417) = -13.196$, $p < 0.001$; Position 3, $t(1874.667) = -5.875$, $p < 0.001$). Indeed, similar to PS characters, when comparing SP characters' performance in fixation position 1 and 3, there was a significant interaction between fixation position and regularity ($F(1, 213) = 11.863$, $p = 0.001$): the regularity effect was stronger when SP characters were presented in fixation position 1 compared with fixation position 3 (Figure 3(c)). Thus, the regularity effect in different fixation locations corresponded well to the entropy level presented in the block where the phonetic radical appeared: the higher the entropy level was, the stronger the regularity effect the model exhibited. Consequently, the interaction between regularity and position of the phonetic radical was strongest when characters were presented in fixation position 1 and the weakest in fixation position 3 (Figure 3(c)).

As for the comparison between SP and PS characters in different regularity and fixation position conditions, since there was no main effect of character type (SP vs. PS), there was no significant difference between the SP and PS characters in various regularity and fixation position conditions, except that in fixation position 1, irregular PS characters had less error than irregular SP characters ($t(251.738) = 4.835$, $p < 0.001$; for the rest, t-test, n.s. See Figure 3).

In a separate simulation, we created an artificial lexicon with the same number of SP and PS characters (i.e. a balanced distribution), in order to examine the baseline behavior of the model when there is no overall information skew in the lexicon; the results reflect the fundamental structural differences between SP and PS characters. This artificial lexicon had 200 SP and 200 PS characters. The character type distribution in both the SP and PS character groups was proportional to the distribution of the SP characters in the real lexicon. Hence, among the 200 characters in either the SP or PS group, there were 74 regular characters (37%), 26 semiregular characters (13%), and 100 irregular characters (50%). Within the 100 irregular characters, 53 characters had the same rime as their phonetic radical, 12 characters had the same onset as their phonetic radical, and 35 characters had a radically different pronunciation from their phonetic radical.

The radicals that comprised the 200 SP characters consisted of 10 semantic radicals that only appeared on the left of the characters, and 40 phonetic radicals. The 200 PS characters consisted of the same 40 phonetic radicals as those in the SP characters, and another set of 10 semantic radicals that only appeared on the right of the characters. The 40 phonetic radicals could appear on either the left or right of a character. The characters in the SP group were randomly generated from different combinations of the left semantic radicals and the phonetic radicals; the semantic radicals of the characters in the PS group had the same combinations with the phonetic radicals as those in the SP group. The training corpus contained all the 400 phonetic compounds and the 40 phonetic radicals. Each character was presented with equal frequency. The test corpus contained the same phonetic compounds but not the phonetic radicals.

The results again showed a significant three-way interaction between fixation position, character regularity, and position of the phonetic radical ($F(2, 792) = 19{,}786$, $p \ll 0.001$ with the Greenhouse-Geisser correction). Figure 4(a) shows the interaction between character regularity and position of the phonetic radical in fixation position 1 and 3. In fixation position 1, SP characters had a stronger regularity effect than PS characters; this phenomenon can be explained by a higher processing demand for SP characters than PS characters, since the phonetic radicals of SP characters were presented in a block with higher entropy (i.e., block 2) compared with those of PS characters (block 1; Figure 4(b)). This higher processing demand pushed the model to a higher level of generalization versus memorization, leading to a stronger regularity effect. In contrast, PS characters had a stronger regularity effect in fixation position 3 than SP characters, since their phonetic radicals were presented in a block with higher entropy. This phenomenon supported the claim that the level of regularity effect in different fixation positions was influenced by the processing demand presented to the model from the given fixation position. It also showed that the three-way interaction we observed when the model was trained with the real lexicon was at least partly due to the fundamental structural differences between SP and PS characters[6].

Behavioral Experiment

Our modeling of Chinese phonetic compound pronunciation showed that the interaction between character regularity and position of the phonetic radical (SP vs. PS characters) was the strongest in fixation position 1, i.e., when the characters were presented just to the left of the fixation, and the weakest in fixation position 3, i.e., when the characters were presented just to the right of the fixation (Figure 3(a)). Since we did not assume any fundamental processing differences between the two sides of the model, this visual field difference emerged purely due to the imbalanced processing demand received on the two sides of the model and the fundamental structural differences between SP and PS character. In order to examine whether human behavior is also influenced by these factors, here we conducted a corresponding Chinese character naming behavioral study. The modeling data showed a gradual change in the interaction between character regularity and position of the phonetic radical from fixation position 1 to fixation position 3 (Figure 3(c)). Thus, to contrast the difference observed between fixation position 1 and 3 in the model, in this behavioral study characters were presented either just to the left (i.e. fixation position 1, the LVF) or to the right of the central fixation (i.e. fixation position 3, the RVF)[7]. The use of error to model response time data has been a standard method in psycholinguistics (e.g., Seidenberg & McClelland, 1989; Plaut et al., 1996; Shillcock & Managhan, 2001; Hsiao & Shillcock, 2004; Hsiao & Shillcock, 2005b). Thus, according to the modeling data, we predict a three-way interaction between character regularity, position of the phonetic radical, and visual field, in participants' naming response times.

Materials

The materials consisted of the same 75 pairs of SP and PS characters used in Hsiao and Shillcock's (2005b) study. Hence, each pair shared the same phonetic radical and was matched in terms of pronunciation and token frequency; the two groups of characters (i.e., SP and PS characters) were matched as closely as possible according to syntactic class, semantic concreteness, and visual complexity of semantic radical as defined by number of strokes. Of the 75 pairs of SP and PS characters, 31 were regular or semiregular and 44 were irregular. Character frequencies were within a mid- to-high range. A further 40 SP and 20 PS filler characters, half regular and half irregular, were also used in the experiment.

Participants

We recruited 16 female and 16 male native Chinese speakers from Taiwan, with similar (university or higher) educational background and normal or corrected vision. All were right-handed according to the Edinburgh handedness inventory (Oldfield, 1971) and with ages matched between the male and female groups. They received a small honorarium for their participation.

Design & Procedure

The design of this study had three within-subject variables: position of the phonetic radical (PS vs. SP), character regularity (regular/semiregular vs. irregular), and visual field (LVF vs. RVF). The dependent variable was the time taken to begin a correct pronunciation. Characters were presented in a standard calligraphic font, each measuring approximately 1 x 1 cm^2 on the screen. Participants sat in front of a screen, at a viewing distance of 115 cm. Hence, each character subtended less than one degree of visual angle and fell within foveal vision. This design was to more closely simulate typical reading behavior (i.e., mostly within foveal vision) and to attenuate any visual acuity difference when a character was presented in the LVF or RVF (Lindell & Nicholls, 2003).

Each naming trial began with two short vertical lines presented on the screen for 500 ms. Participants were told to look at the midpoint between the two lines. The two lines were followed by a 150 ms presentation of the target character, which did not allow time for refixation[8]. The target character was presented immediately either to the right or to the left of the initial fixation. Occasionally a 9 pt. digit was presented, instead of a character, exactly between the two lines where participants should be fixating, to ensure that participants were fixating the right place; the digit was only presented for 90 ms. Data from any participant who did not report the digits to an acceptable accuracy were rejected (e.g., Hsiao & Shillcock, 2005b; Hsiao et al., 2007; cf. Brysbaert, 1994)[9]. After each presentation of a target character or a digit, participants were asked to name the character or digit as fast and as accurately as possible. We measured the response time as the time difference between the onset of the character presentation and the onset of the participant's pronunciation. The stimulus was replaced by a mask after the presentation; the mask disappeared after the onset of the participant's pronunciation. The screen then turned blank until the experimenter pressed a button to start the next trial. Participants were put into four groups, with males and females evenly distributed. The materials presented to the four groups were counterbalanced along two dimensions: presentation order of each pair of PS and SP characters (i.e., the PS character or the SP character first) and presented visual field for each character. During the experiment, the SP and PS characters in the same pair did not appear in the same block or in the same visual hemifield to minimize priming effects. Characters in each block were presented in a random order.

Results

The results of the behavioral experiment showed that there was a significant three-way interaction between visual field, character regularity, and position of the phonetic radical ($F(1, 30) = 4.484$, $P < 0.05$; Figure 5): there was a significant interaction between character regularity and position of the phonetic radical in the LVF ($F(1, 31) = 4.874$, $P < 0.05$), but not in the RVF ($F < 1$). This result hence matched well with the model's predictions, suggesting the influence of perceptual learning in accounting for this visual field difference in the human data[10]. Because of the overall rightward information skew and the fundamental structural differences between SP and PS characters, when PS characters were presented in the LVF, individual mappings between orthography to phonology could be processed without generalization, and thus there was no regularity effect when PS characters were presented in the LVF ($t(31) = 0.311$, n.s.); when they were presented in the RVF, the denser mapping problem demanded more generalization, and thus there was a significant regularity effect when PS characters were presented in the RVF ($t(31) = -2.562$, $p < 0.05$; Figure 5). In contrast, when SP characters were presented in the LVF, there was a significant regularity effect ($t(1, 31) = -2.799$, $p < 0.01$); when SP characters were presented in the RVF, the regularity effect did not reach significance ($t(1, 31) = -1.315$, $p = 0.198$; Figure 5). This result is consistent with the modeling data, which showed that SP characters had a weaker regularity effect in fixation position 3 compared with fixation position 1 (Figure 3(c)).

In order to more closely compare the behavioral data with the modeling data, in a separate analysis of the modeling data, after the model was trained with all characters in the training corpus, only characters used in the behavioral experiment were selected for the analysis, and only data in fixation position 1 and 3 (i.e. the LVF and RVF) were analyzed. The results showed a main effect of fixation position ($F(1, 142) = 12.427$, $P = 0.001$): the model had better performance when characters were presented in fixation position 1 (the LVF) than fixation position 3 (the RVF). In addition, similar to the behavioral data, there was a three-way interaction between fixation position, character regularity, and position of the phonetic radical ($F(1, 142) = 8.435$, $p < 0.01$; Figure 6): there was a tendency of an interaction between character regularity and position of the phonetic radical in fixation position 1 (the LVF: $F(1, 142) = 3.081$, $p = 0.081$), but not in fixation position 3 (the RVF: $F < 1$, n.s.). When examining the regularity effect in different conditions separately, there was a significant regularity effect when PS characters were presented in fixation position 3 (the RVF, $t(73) = -2.286$, $p < 0.05$), but not in fixation position 1 (the LVF, $t(73) = -0.399$, n.s.; see Figure 6); in contrast, for SP characters, there was a significant regularity effect when they were presented in fixation position 1 (the LVF, $t(50.793) = -3.012$, $p < 0.01$), but not in fixation position 3 (the RVF, $t(73) = -0.707$, n.s.; see Figure 6). This three-way interaction between fixation position, character regularity, and position of the phonetic radical in the modeling data thus was consistent with the behavioral data (Figure 6), suggesting the influence of perceptual learning in accounting for the visual field difference in the behavioral data.

In contrast to the modeling data, there was no main effect of visual field in the human behavioral data ($F < 1$). The model predicted a LVF advantage due to the overall rightward information skew. It is possible that in the human data this LVF advantage was offset by the fact that the RVF has direct access to the LH, which is superior in phonological processing. In contrast, since here we aimed to examine whether visual field differences can emerge purely due to perceptual learning, our model did not assume this difference in phonological processing between the two hemispheres, and thus the LVF advantage due to perceptual learning was not offset by the RVF advantage in phonological processing. Consistent with this speculation, it has been shown that Chinese character recognition involves an interplay between a LVF advantage for orthographic processing (such as in tachistoscopic identification tasks; e.g. Tzeng et al., 1979; Cheng & Yang, 1989) and a RVF advantage for phonological processing (such as in naming tasks; e.g., Yang & Cheng, 1999; Weekes & Zhang, 1999). In addition, our modeling data suggest that the three-way interaction between character regularity, position of the phonetic radical, and visual field observed in the human data does not require phonological processing being LH lateralized; this effect can emerge purely due to perceptual learning (and so can the

LVF advantage of orthographic processing observed in the Chinese character recognition literature).

The model also failed to account for the main effect of position of the phonetic radical in the human data: Participants were faster in naming SP characters compared with PS characters, regardless of the visual field ($F(1, 31) = 38.977$, $p < 0.001$); there was a significant difference between the SP and PS characters in all different regularity and fixation position conditions (LVF, regular SP vs. PS characters, $t(31) = 4.721$, $p < 0.001$; LVF, irregular SP vs. PS characters, $t(31) = 2.497$, $p < 0.05$; RVF, irregular SP vs. PS characters, $t(31) = 3.207$, $p < 0.01$), except for the condition when regular SP and PS characters were presented in the RVF (n.s.; see Figure 5). This effect may be due to the dominance of SP characters in the lexicon compared with PS characters. This difference between the human data and the modeling prediction may be because in the modeling, characters were presented to the model according to their log frequency instead of the original frequency[1], and thus it may have reduced the dominance of SP characters in the lexicon. Future work will examine whether training the model with raw frequency of the characters will result in a better fit with human data. This difference between the human data and the model prediction may also be because the model did not take the LH-lateralized phonological processing into account. For example, the phonetic radical of an SP character may appear in the RVF more often during learning to read compared with that of an PS character, and thus the processing of SP characters may be facilitated by the LH phonological processing more than PS characters. Also, SP characters have a larger percentage of regular characters than PS characters, and thus SP character processing may benefit more from LH phonological modulation (e.g., the *phonological mapping hypothesis*, Maurer & McCandliss, 2007) than PS characters. These speculations require further examinations.

Note that although the model predictions differed from the human data in the main effects of visual field and character type (SP vs. PS) as mentioned above, the model proposed here was not expected to account for every aspect of the human data; in contrast, the purpose of the study was to examine possible visual field differences that can emerge in a model that does not assume hemispheric processing difference. Thus, it is expected that the model cannot account for effects in human data that are mainly due to fundamental hemispheric processing difference, such as the LH-lateralized phonological processes. Our modelling data showed a three-way interaction between visual field, position of the phonetic radical, and character regularity, suggesting that visual field difference can emerge purely due to asymmetric input information structure. Our human data showed a similar three-way interaction; this result suggests that the visual field difference (i.e. the three-way interaction) observed in the human data can be accounted for by a model that does not assume hemispheric processing difference; in other words, this visual field difference emerged mainly due to the information structure of the characters, as opposed to fundamental processing differences between the two hemispheres.

DISCUSSION

Through modeling Chinese character pronunciation, here we have shown that, given a symmetric processor, in which no fundamental processing difference between the two sides of the model (i.e. by analogy with the two hemispheres) is assumed, hemispheric asymmetry, or more precisely, visual field differences, emerge purely due to asymmetric information structure of the input stimuli, suggesting the influence of perceptual learning. Corresponding human behavioral data are consistent with the modeling prediction. This study thus provides strong evidence showing that visual field differences observed in human data do not always imply fundamental hemispheric processing differences; they can emerge purely from perceptual learning, that is, the information structure of the visual stimuli that participants have long been exposed to. Chinese SP and PS characters provide an important opportunity to examine this phenomenon, because of the fundamental structural differences in information between SP and PS characters and the overall information skew in the lexicon.

In our computational modeling with Chinese SP and PS characters, we show that when the network architecture is completely symmetrical, there is a three-way interaction between visual field, position of the phonetic radical (SP vs. PS), and character regularity. When there is a balanced distribution between SP and PS characters in the lexicon (i.e., no overall information skew), as in the artificial lexicon, the fundamental structural differences between SP and PS characters cause a stronger regularity effect for SP characters in the LVF and stronger regularity effect for PS characters in the RVF. When the distribution between SP and PS characters is unbalanced, as in the real lexicon, a similar three-way interaction is observed; the overall rightward information skew demands more processing load in the RVF, and pushes both SP and PS characters to a similar level of generalization. As the result, there is an interaction between position of the phonetic radical and character regularity in the LVF, but not in the RVF. Since the model architecture is completely symmetric, this visual field difference observed after training must be due to asymmetric connection weights developed in the two sides of the model as a consequence of learning the asymmetric information structure of the input stimuli.

In addition, the modeling data show that the level of regularity effect is influenced by the amount of information (defined by entropy) received in the block in which the phonetic radicals appear during training. For SP characters, the regularity effect is weaker when they are presented in the RVF than the LVF (Figure 5 and 6), because when they are presented in the RVF, their phonetic radical appears in an input block (block 4 in Figure 2 and 3) with a lower entropy compared with when they are presented in the LVF (block 2 in Figure 2 and 3). In contrast, PS characters have a weaker regularity effect when they are presented in the LVF compared with the RVF (Figure 5 and 6), since in the RVF presentation their phonetic radicals appear in block 3, which has higher entropy than block 1 in the LVF (Figure 2 and 3).

The modeling predictions are consistent with the human data. In the corresponding Chinese character naming experiment, in which characters are presented either just to the left or to the right of the central fixation as in the model, we show a similar three-way interaction as the modeling data. This result hence suggests that not all visual field differences observed in behavioral data imply fundamental processing differences between the two hemispheres; it could be due to perceptual learning, that is, the information structures of the word stimuli to which the readers have long been exposed. This perceptual learning account may also partly explain the attentional advantage account (Mondor & Bryden, 1992): for English words, contrary to Chinese characters, there is more information on the left of the words (e.g., Shillcock et al., 2000), and hence the LVF may have received more processing demands; consequently the LVF/RH requires more attentional resources. Thus, this perceptual learning account can more readily accommodate data from both English and Chinese studies than can the attentional advantage model.

The current model follows the general principles governing visual recognition in the human visual system (McCandliss et al, 2003), from the early visual area/lateral occipital region (the input layer), the VWFA (the hidden layer), to the temporal regions anterior to the VWFA for phonological processes (the output layer). Since the model training involves weight modification on the connections between the layers, the modelling data suggest that this perceptual learning effect extends far into the connections anterior to the VWFA. This effect is consistent with the perceptual learning literature showing that discrimination training of complex visual forms can lead to changes in higher cortical areas such as inferior temporal (IT) region (e.g., Sakai & Miyashita, 1994; see Gilbert, Sigman, & Crist, 2001). Note that it is the model's assumption that the process of visual word recognition involves the VWFA and the temporal regions anterior to the VWFA, as suggested by recent brain imaging data (e.g., McCandliss et al., 2003). Also, the model implements a general learning algorithm, gradient decent (or more specifically, back-propagation), and does not assume any specific cognitive strategy in learning the pronunciation of the character stimuli.

The contrasting structures of Chinese SP and PS characters and the separation of semantic and phonetic components in Chinese characters provide a unique opportunity to show this perceptual learning effect. It remains an open question whether a similar perceptual learning effect can also be observed in other languages. For example, in contrast to Chinese characters, words in alphabetic languages such as English do not have separate semantic and phonetic components; the phonological information is spread over the whole word. In addition, they have longer word lengths than Chinese characters, and thus readers have a tendency to fixate at a particular position more often during reading (preferred viewing locations; Rayner, 1979); these preferred viewing locations may also be influenced by the information profile of words in the lexicon (e.g., Shillcock et al., 2000). In short, the influence of perceptual learning in reading behavior may depend on the characteristics of the writing system, and thus it requires further investigation whether the effect observed here in Chinese character processing can also be observed in the processing of words in other languages.

In conclusion, there have been several factors proposed that may account for visual field differences observed in visual word recognition, such as the RH superiority in handling holistic pattern recognition and the LH superiority in phonological processing, the differential frequency bias proposed in the Double Filtering by Frequency theory (Ivry & Robertson, 1998), the coarse- and fine-semantic coding difference between the two hemispheres (Jung-Beeman, 2005), and visual acuity, which drops dramatically from the centre of fixation to the periphery (Nazir, O'Regan, & Jacobs, 1991). Here we have provided strong evidence for the influence of perceptual learning: the information structures of the word stimuli to which the readers have long been exposed. The contrasting structures of Chinese SP and PS characters provide a unique opportunity for this examination; computational modeling also makes it possible to tease apart the factors that would be difficult to separately manipulate in human subject studies, such as the fundamental hemispheric processing differences in the human brain. It remains unclear how these different factors interact with each other. Thus, further investigation is required for a full understanding of how the two hemispheres coordinate information presented in the two visual hemifields in visual word recognition.

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Footnote

[1] The logarithmic frequency compression technique has been frequently used in computational modeling of word processing to reduce the impact of word frequency on the knowledge learned by the model. See Plaut et al. (1996) for more discussion.

[2] This phenomenon may be because the length of a character is too short for the effect to emerge (see Tsai & McConkie, 2003).

[3] In the current modeling the test and training sets were overlapped, since the purpose of the modeling was to examine whether the model exhibited similar behavior as skilled readers, such as the regularity effect, after learning the same characters as skilled readers, instead of testing the model's capacity to generalize to novel characters. In computational models of visual word recognition (e.g., Shillcock & Monaghan, 2001; Plaut, McClelland, Seidenberg, & Patterson, 1996), the generalization capacity of the model can be tested by examining its capacity to process pronounceable nonwords (pseudo-words), e.g., pronounce pseudo-words according to regular pronunciation rules as skilled readers do (e.g., Plaut et al., 1996). To test this generalization capacity of the current model, in a separate test, after training we tested the model with novel combinations of semantic and phonetic radicals (i.e. pseudo-characters) and examined the output generated by the model. We found that the model was able to generate a regular pronunciation according to the phonetic radical as skilled readers do. Future work will use a computational model that takes raw images as input (e.g., the face recognition model used in Hsiao et al., 2008) instead of stroke pattern encodings to enable testing the model's generalization ability with images of character in different fonts.

[4] In repeated-measures designs, Greenhouse-Geisser correction can be applied to produce a valid F-ratio when data violate the sphericity assumption. The sphericity

assumption refers to the hypothesis that the variances of differences between conditions are equal.

[5] Note that PS characters also have a smaller percentage of regular characters than SP characters; it may partly explain the weaker regularity effect for PS characters.

[6] In separate simulations, we observed a similar three-way interaction in a typical split-fovea model, in which the mapping was mediated through two hidden layers connecting to the two visual hemifields respectively (see, e.g., Shillcock & Monaghan, 2001; Hsiao & Shillcock, 2005a), for both the real and the artificial lexicons. This result suggests that this three-way interaction was mainly due to the information structure of the stimuli, rather than the network architecture (i.e., whether foveal representation is split and processed separately or not).

[7] Also, the behavioral data of naming SP and PS characters when characters were centrally presented (i.e. fixation position 2) have been reported in Hsiao & Shillcock (2005b); the data showed a sex difference that can be accounted for by the difference between the split fovea model and the non-split model.

[8] Latency of saccade production normally takes about 200 ms to initiate, and a saccade typically lasts for 20 to 30 ms under normal reading conditions. Although it has been shown that in some specific oculomotor tasks, there is a distinct distribution of saccades with production latencies as short as 100 ms (express saccades; see, e.g., Fischer and Ramsperger, 1984), this effect does not seem to generalize to normal reading conditions (e.g., Inhoff, Topolski, Vitu, & O'Regan, 1993; Liversadge et al., 2003). As the purpose of the current study was to measure participants' naming response times instead of perceptual accuracy under extreme presentation conditions, the presentation time 150ms was chosen so that participants had ample time to recognize characters, according to previous visual word recognition studies (e.g.,

Hsiao & Shillcock, 2005b; Hsiao, Shillcock, & Lee, 2007; Brysbaert, 1994; Hunter, Brysbaert, & Knecht, 2007).

[9] Despite the stringent measures used in this method to ensure participant's eye fixations, there may still be noise introduced in the exact positioning of participants' eye fixations. A better way to ensure participants' eye fixations may be to use a high-resolution eye tracker to more effectively monitor participants' eye fixations.

[10] The use of error to model response time data has been a standard method in psycholinguistics (e.g., Seidenberg & McClelland, 1989). Also, the regularity effect in Chinese character naming was usually observed in the response time data rather than in naming accuracy data (e.g., Hue, 1992; cf. Jared, McRae, & Seidenberg, 1990), since participants' naming accuracy was usually at the ceiling level. Thus, in the current study, the response time data were analyzed, and it is a limitation of the model to account for RT data by accuracy data. Indeed, since the characters used in the current study were all within mid- to high- frequency range, participants all had very high naming accuracy (~94%). An ANOVA analysis on the accuracy data revealed a significant main effect of character type ($F(1, 31) = 13.508$, $p = 0.001$): participants were more accurate in naming SP characters than PS characters. In addition, there was a significant interaction between regularity and character type ($F(1, 31) = 8.003$, $p < 0.01$): Participants were more accurate in naming regular SP characters than irregular SP characters; this effect was not observed in PS characters. The three-way interaction between character type, regularity, and visual field that was observed in the RT data was not observed in the accuracy data. The absence of this effect may be due to a ceiling effect since participants had high naming accuracy. Future work will examine whether this effect can be obtained in accuracy when the naming task is

more difficult, e.g., in naming low frequency characters, or with a shorter presentation time.

Figure 1. Examples of Chinese SP and PS characters. The two characters have the same phonetic radical and the same pronunciation [coi3] in Pinyin.

Figure 2. Our (non-split) model of Chinese character recognition. (a) Model architecture. (b) Three fixation positions in the input layer.

Figure 3. Modeling results: (a) Model's performance in three different fixation positions. (b) Entropy analysis of the four blocks in the input layer during training. (c) Interaction between character regularity and position of the phonetic radical in fixation position 1, 2, and 3. The error bars show standard errors.

Figure 4. Modeling results with the artificial lexicon: (a) Interaction between character regularity and position of the phonetic radical in fixation position 1, 2, and 3 when the model was trained with the artificial lexicon. The error bars show standard errors. (b) Entropy analysis of the four slots in the input layer for the models trained with the artificial lexicon.

Figure 5. Top: Human behavioral data showed a three-way interaction among visual field, position of the phonetic radical, and character regularity. Bottom: Modeling data also showed a similar three-way interaction. The error bars show standard errors (* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$).

Figure 6. Corresponding modeling data; the model was trained with all characters in the corpus and tested with the same characters used in the behavioral study. The error bars show standard errors (+ $p < 0.1$; * $p < 0.05$; ** $p < 0.01$).

Figure 1

採 彩

S P P S

Figure 2

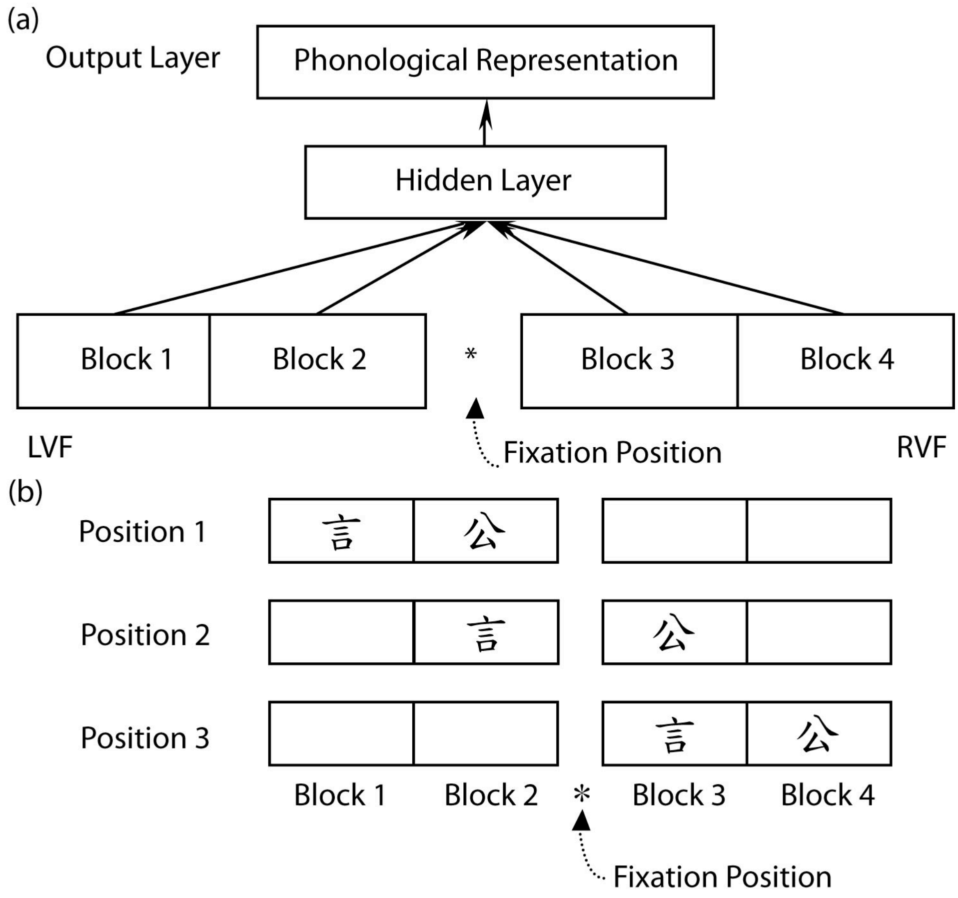
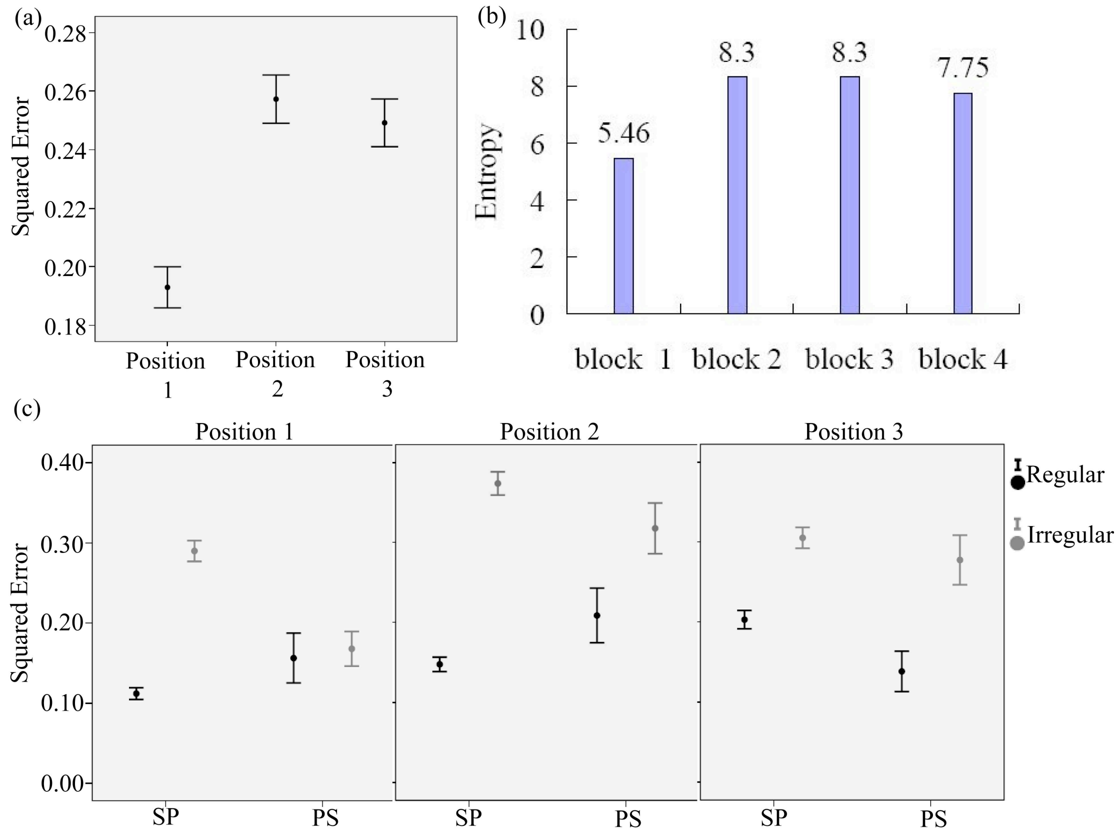

(a)
Output Layer
Phonological Representation
Hidden Layer
Block 1
Block 2
*
Block 3
Block 4
LVF
Fixation Position
RVF
(b)
Position 1
言
公
Position 2
言
公
Position 3
言
公
Block 1
Block 2
*
Block 3
Block 4
Fixation Position

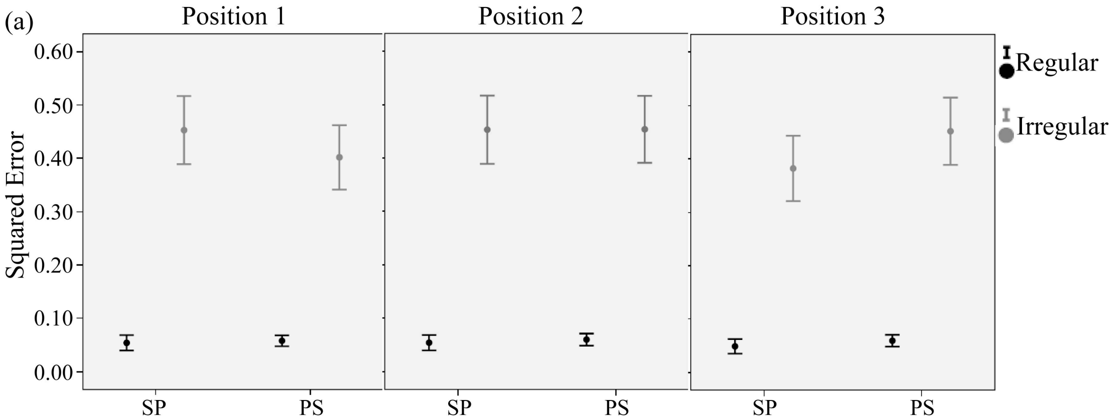
Figure 3



(a)
0.28
0.26
0.24
0.22
0.20
0.18
Squared Error
Position 1
Position 2
Position 3
(b)
10
8
6
4
2
0
Entropy
5.46
8.3
8.3
7.75
block 1
block 2
block 3
block 4
(c)
Position 1
Position 2
Position 3
0.40
0.30
0.20
0.10
0.00
Squared Error
SP
PS
SP
PS
SP
PS
Regular
Irregular

Figure 4

(a)


Position 1
Position 2
Position 3
Regular
Irregular
Squared Error
0.60
0.50
0.40
0.30
0.20
0.10
0.00
SP
PS
SP
PS
SP
PS

(b)

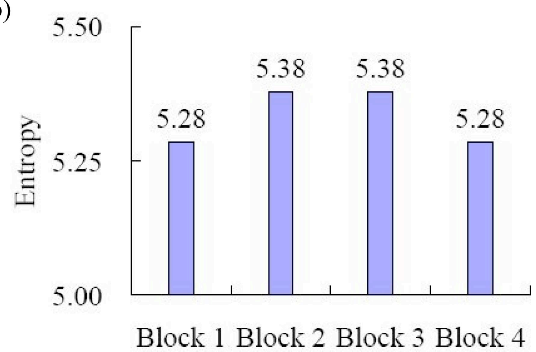
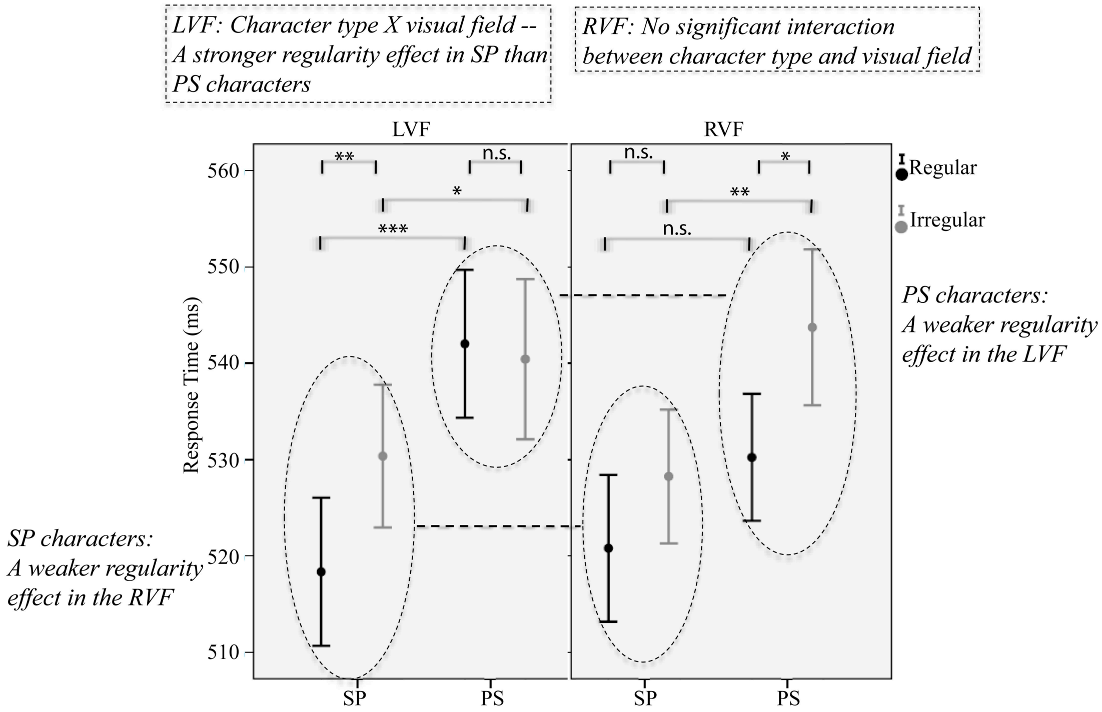

5.50
5.25
5.00
Entropy
5.28
5.38
5.38
5.28
Block 1
Block 2
Block 3
Block 4

Figure 5

Behavioral data



Modeling data (with all SP and PS characters in the lexicon)

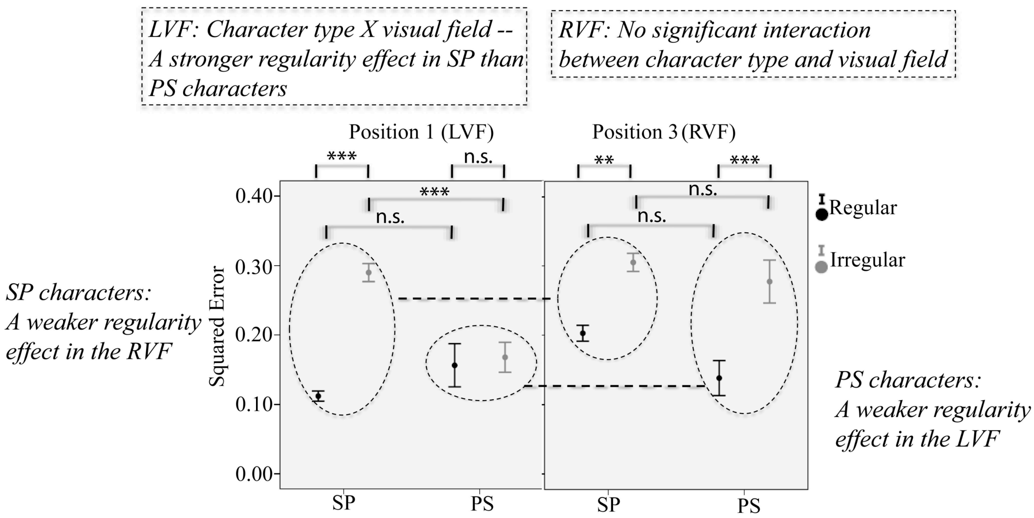


Figure 6

Modeling data (with characters used in the behavioral study only)