Supplemental Materials

The Processing Architectures of Whole-Object Features: A Logical-Rules Approach

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Similarity Ratings: Multidimensional Scaling

Method

Amazon Mechanical Turk was used to obtain similarity ratings for the stimuli shown in Figure 2. For each stimulus set, a single Human Intelligence Task (HIT) was created on Amazon Mechanical Turk with 25 assignments. We restricted access to the HIT by requiring users to have at least a 90% acceptance rate (i.e., 90% of a user's completed HITs were accepted by the requester), to have completed at least 1000 approved HITs, and to be located in the United States. Participants were paid $2.00 USD to complete the task, which took approximately 25 minutes to complete.

On each trial, a pair of stimuli was presented in the upper-left and upper-right of the screen. Subjects rated the similarity of each pair from 1 "least similar" to 8 "most similar". Subjects were instructed to try to use the full range of ratings and were given examples of high, medium, and low similarity pairs of stimuli before commencing the task. Participants were further instructed to utilize both perceptual dimensions when determining their ratings (i.e., saturation and orientation). For each condition, there were 36 unique pairings of the 9 stimuli. Each pair was presented six times for each subject; the order of presentation was randomized, as was the left-right presentation of each stimulus. The experiment was self-paced.

Results

We computed the averaged similarity rating for each pair of stimuli and found the two-dimensional scaling solutions for each condition. This was done by fitting the averaged ratings using a model that assumed a negative linear relationship between the predicted similarity ratings and the distance between the estimated coordinates. To find the best fitting coordinates, we minimized the sum-of-squared deviations between the predicted and participant ratings from 100 starting points chosen to span the coordinate space. The best fitting solution was constrained such that each of the nine coordinates fell along a 3 x 3 grid. This model utilized six free parameters and allowed only the distance between values on each of the two perceptual dimensions to vary. The estimated two-dimensional-scaling solution accounted for over 97% of the variance in the averaged ratings for each of the three conditions. The rotated solutions for each of the three conditions are presented in Figure S1. In addition, each scaling solution was best fit assuming a city-block distance metric between each coordinate, which provides initial evidence that whole-object features are analysed separably (Nosofsky, 1992; Shepard, 1964, 1987).

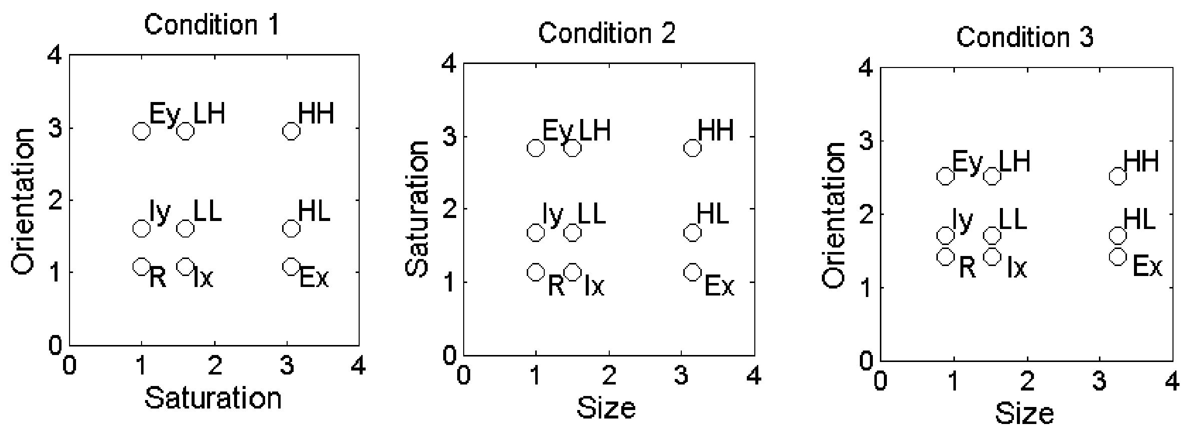

Figure S1. Multidimensional scaling solutions for stimuli in the three conditions.

Survivor Function Tests of Selective Influence

In order to verify the observations of the SIC patterns, we applied statistical tests for the survivor functions and the SIC function using the Systems Factorial Technology package in R (see Houpt, Blaha, McIntire, Havig, & Townsend 2014). For each participant, we first utilized a series of one-sided Kolmogorov-Smirnov tests of distribution ordering (Houpt & Townsend, 2010) to check for the expected ordering of the survivor functions (i.e., stochastic dominance; Heathcote, Brown, Wagenmakers & Eidels, 2010). These tests examine whether S_{HH} is faster at all times than S_{HL} and $S_{LH,}$ and that S_{LL} is slower at all times than S_{HL} and S_{LH}. This analysis is critical because violation of stochastic dominance invalidates the assumptions of the MIC and SIC analyses.

For all participants in all three conditions, no violations of stochastic dominance were observed (all $p < 0.01$).

Bootstrapped MICs

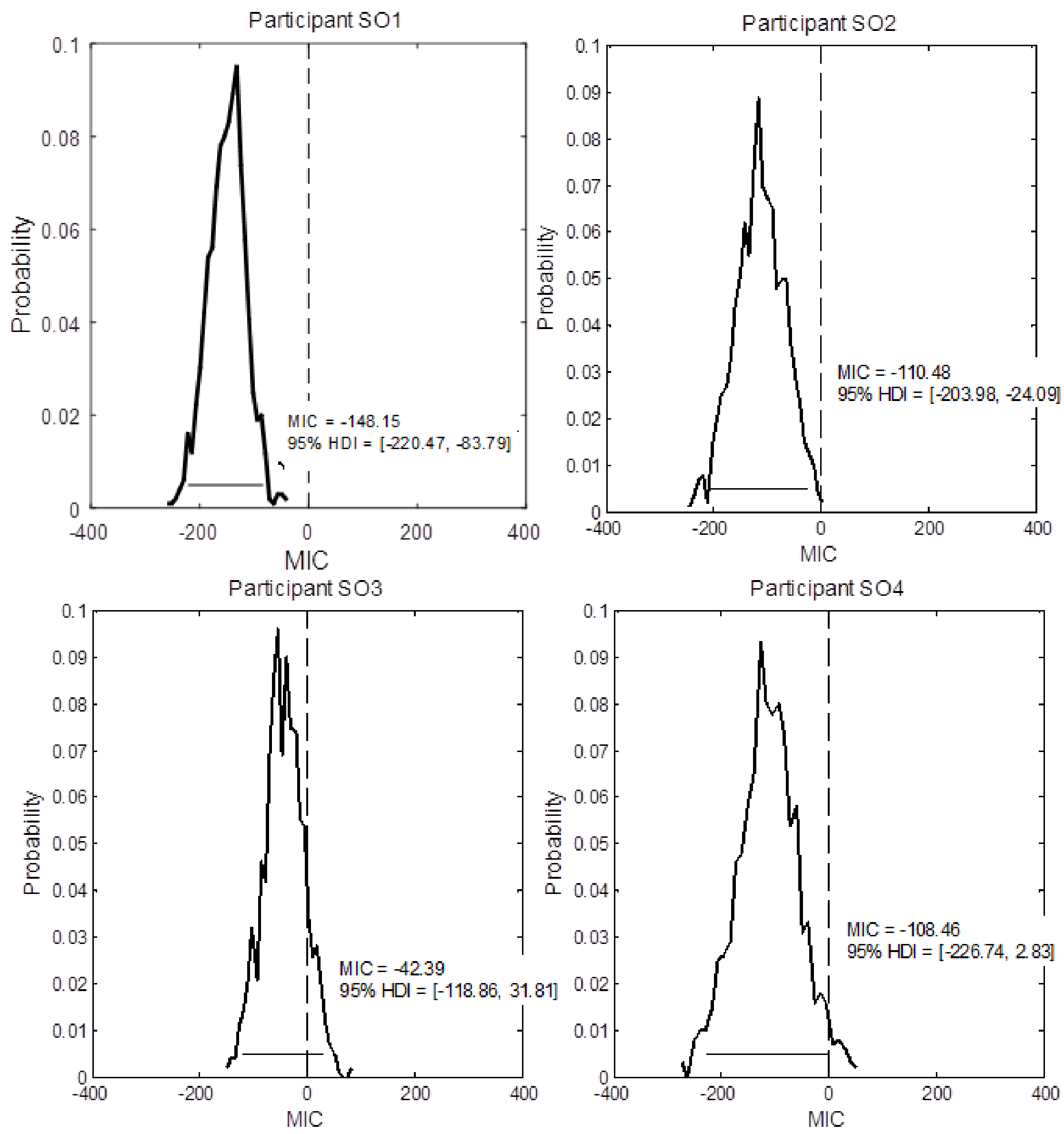

Figure S2. Bootstrapped MICs for each participant in the Saturation-Orientation condition. 95% Highest Density Intervals (HDIs) are shown (the solid horizontal line). The vertical dotted line marks the point at which MIC = 0. Note that these estimates are obtained by bootstrapping and are not posterior density estimates.

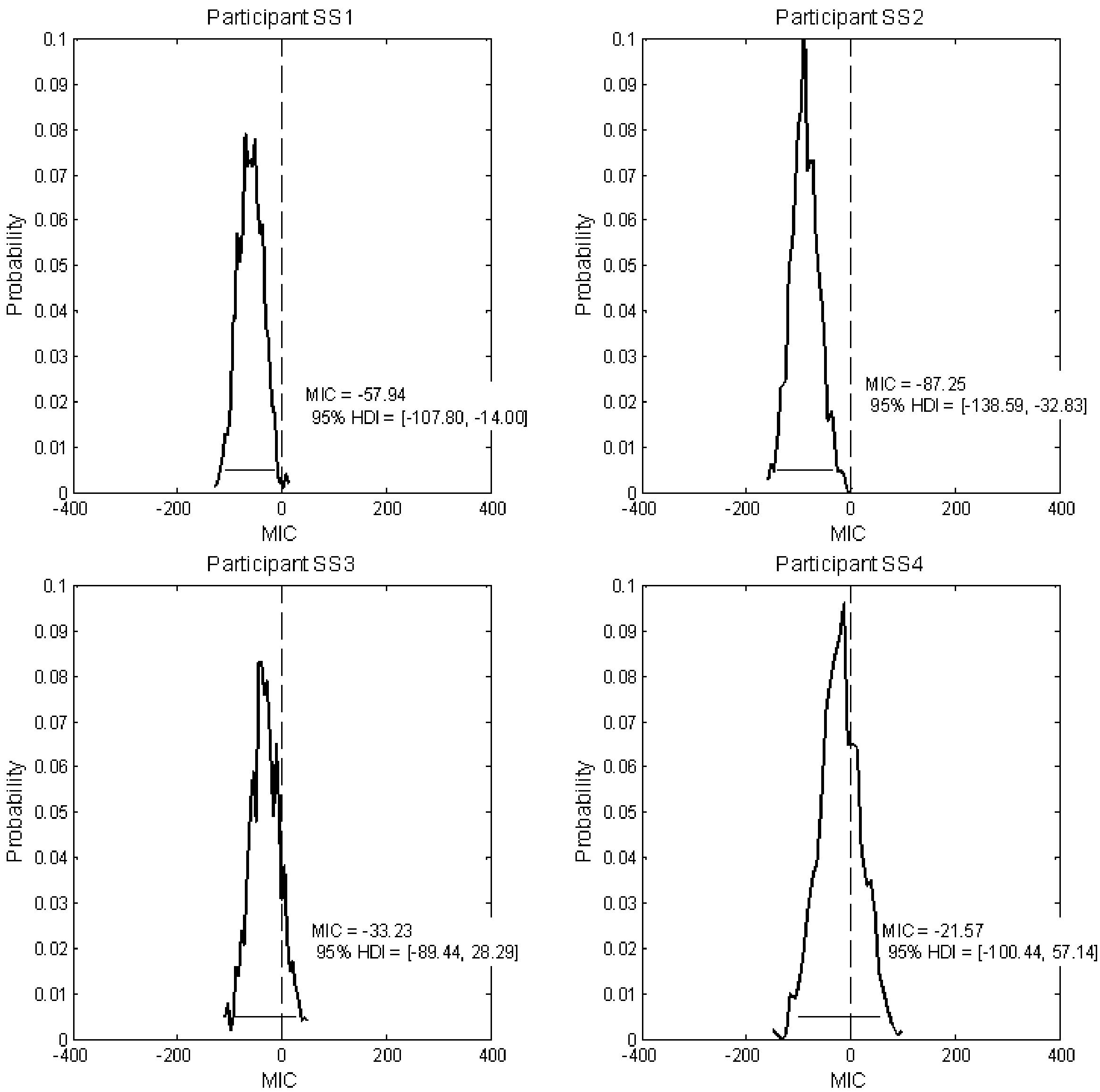

Figure S3. Bootstrapped MICs for each participant in the Size-Saturation condition. 95% Highest Density Intervals (HDIs) are shown (the solid horizontal line). The vertical dotted line marks the point at which MIC = 0. Note that these estimates are obtained by bootstrapping and are not posterior density estimates.

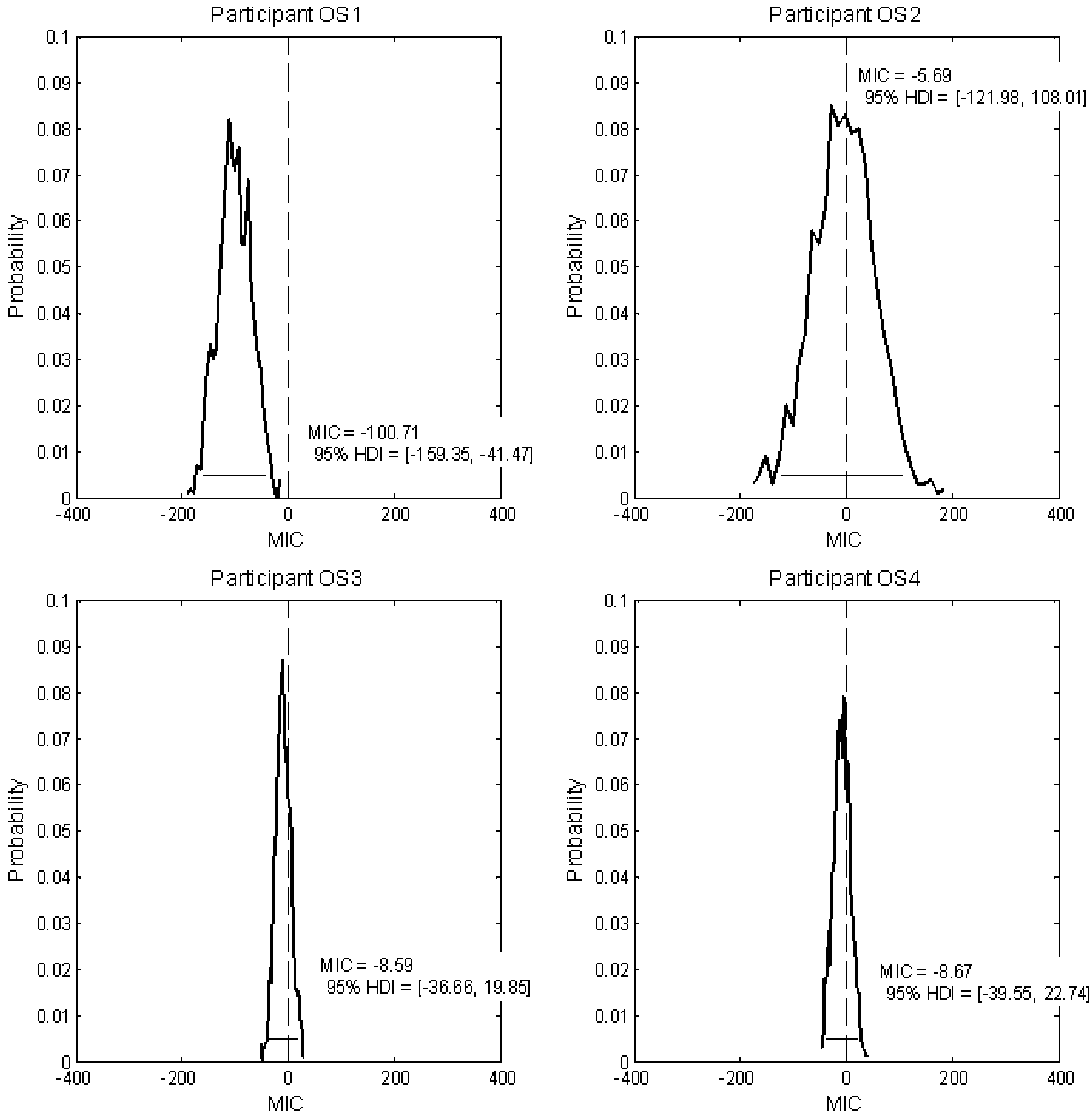

Figure S4. Bootstrapped MICs for each participant in the Orientation-Size condition. 95% Highest Density Intervals (HDIs) are shown (the solid horizontal line). The vertical dotted line marks the point at which MIC = 0.

Model Fitting

Model Parameterization and Description of the Logical-Rule Models

The free parameters of the logical-rule models are described in detail by Fifić, Little & Nosofsky (2010). A simplifying assumption of all logical-rule models is that all stimuli have identical perceptual-effect variability along dimension *x* (and likewise for dimension *y*). To allow for the possibility of overall differences in the discriminability between the dimensions, the perceptual effects are allowed to be a separate free parameter for each dimension (σ_x and σ_y, respectively). Further, to implement the perceptual-sampling process that drives the random-walk, the participant establishes a decision bound along each dimension (D_x and D_y), and criteria representing the amount of evidence needed for making an A (target category; +*A*) or B (contrast category; +*B*) decision on each dimension. A scaling parameter, *k*, is used to transform the number of steps in each random walk into milliseconds. Each model also assumes that there is a residual base time for non-decision processes (e.g., motor movements), which is log-normally distributed with a mean μ_R and variance σ^2_R. Finally, the serial self-terminating model requires a free parameter, p_x, representing the probability that dimension *x* will be the first-processed dimension on each individual trial. Hence, each of the base logical rule models has nine free parameters except for the serial self-terminating model, which has ten.

The mixed serial-parallel model additionally assumes a probability, p_s, that processing on a given trial is serial, and a probability of 1 - p_s that processing is parallel. To reduce the number of free parameters necessary for fitting the mixed model, we assume identical random-walk criteria, decision-boundary positions, and residual time distributions for both serial and parallel component processes. However, to allow for different processing rates between the two processes across trials, the dimensional variances for the serial processes were scaled by a multiplier (m_σ) to yield the variances for the parallel process. We also allowed the scaling parameter for the serial process random-walks (k_p) to differ from the parallel process random-walks (k_s). So, in total, the mixed serial-parallel model has 13 free parameters.

Finally, we also fit a *free stimulus drift rate* model in which the probability of taking a step toward the category +A boundary was a freely estimated parameter for each item. As shown in Fifić et al. (2010), this model is highly flexible and contains the EBRW (Nosofsky & Palmeri, 1997), stochastic GRT (Ashby, 2000), and the logical rules coactive model as a special case. This model is unconstrained by any of the stimulus representation assumptions that are assumed by the remaining models. Consequently, this model can flexibly allocate its drift rate to achieve the best fit to the RT distribution data. Nonetheless, because this model contains additional free parameters (i.e., 15 in total), when penalized for complexity (i.e., using BIC see below), the model may not fit as well as its less flexible competitors. Furthermore, as shown in Fifić et al. (2010), when the data were truly generated by an alternative independent architecture model (i.e., serial or parallel), the free drift rate model is unable to fit as well as the an independent architecture. Thus, this model provides a strong test of coactivity allowing us to assess the extent to which some of the observed contrast category RT patterns (i.e., when the interior stimulus was faster than the exterior stimulus) are truly evidence for coactivity.

RT distribution predictions for the best fitting model

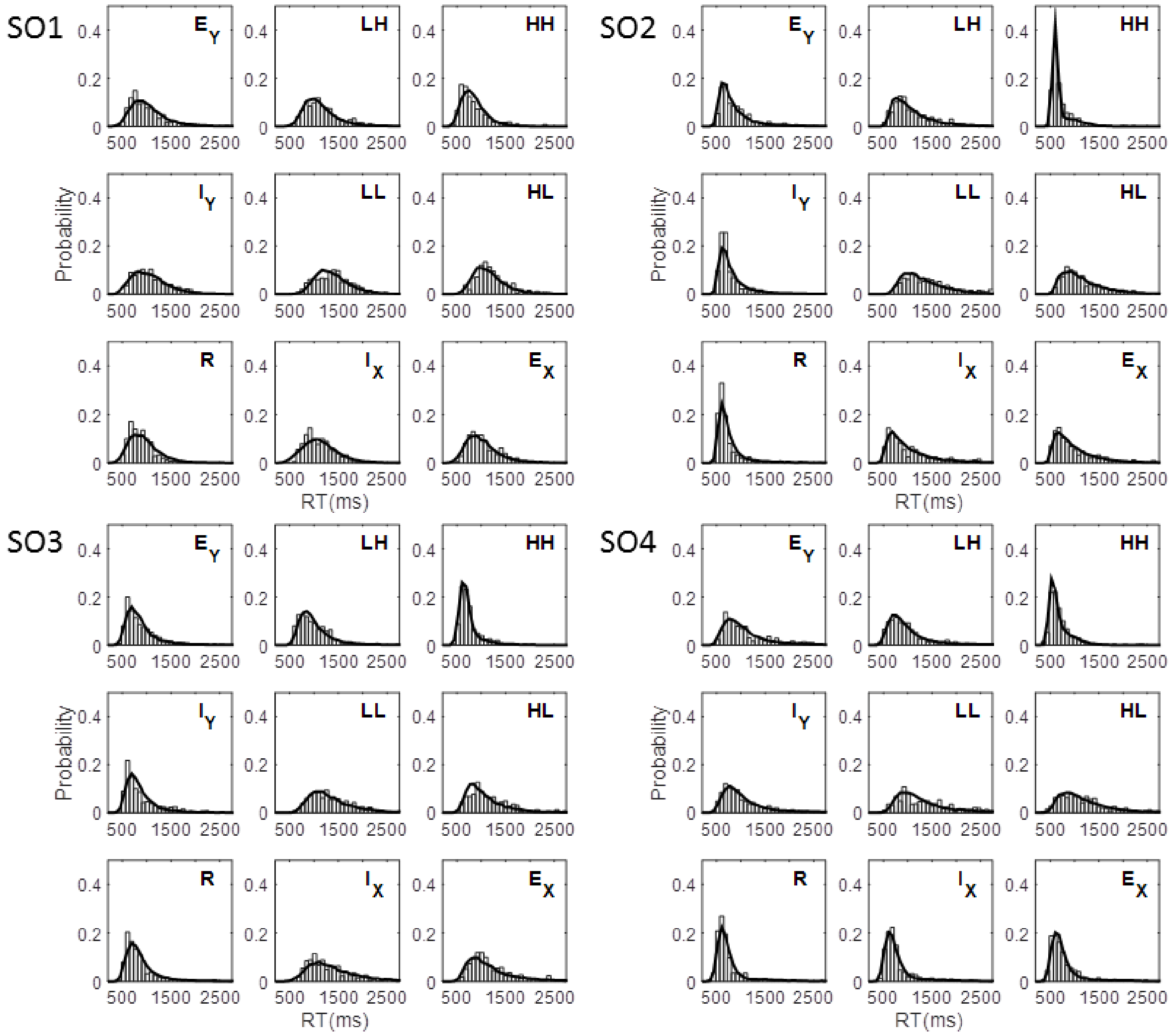

Figure S5. Fit (solid line) of the mixed serial-parallel self-terminating model to the response time (RT) distribution data (open bars) of the individual subjects in in the Saturation & Orientation condition (SO). Each cell of each panel shows the RT distribution associated with an individual stimulus. Within each panel, the spatial layout of the stimuli is the same as in Figure 2. Stimuli are coded as high (H) and low (L) discriminability items (target category; A) as well as internal (I), external (E), and redundant (R), stimuli (contrast category; B).

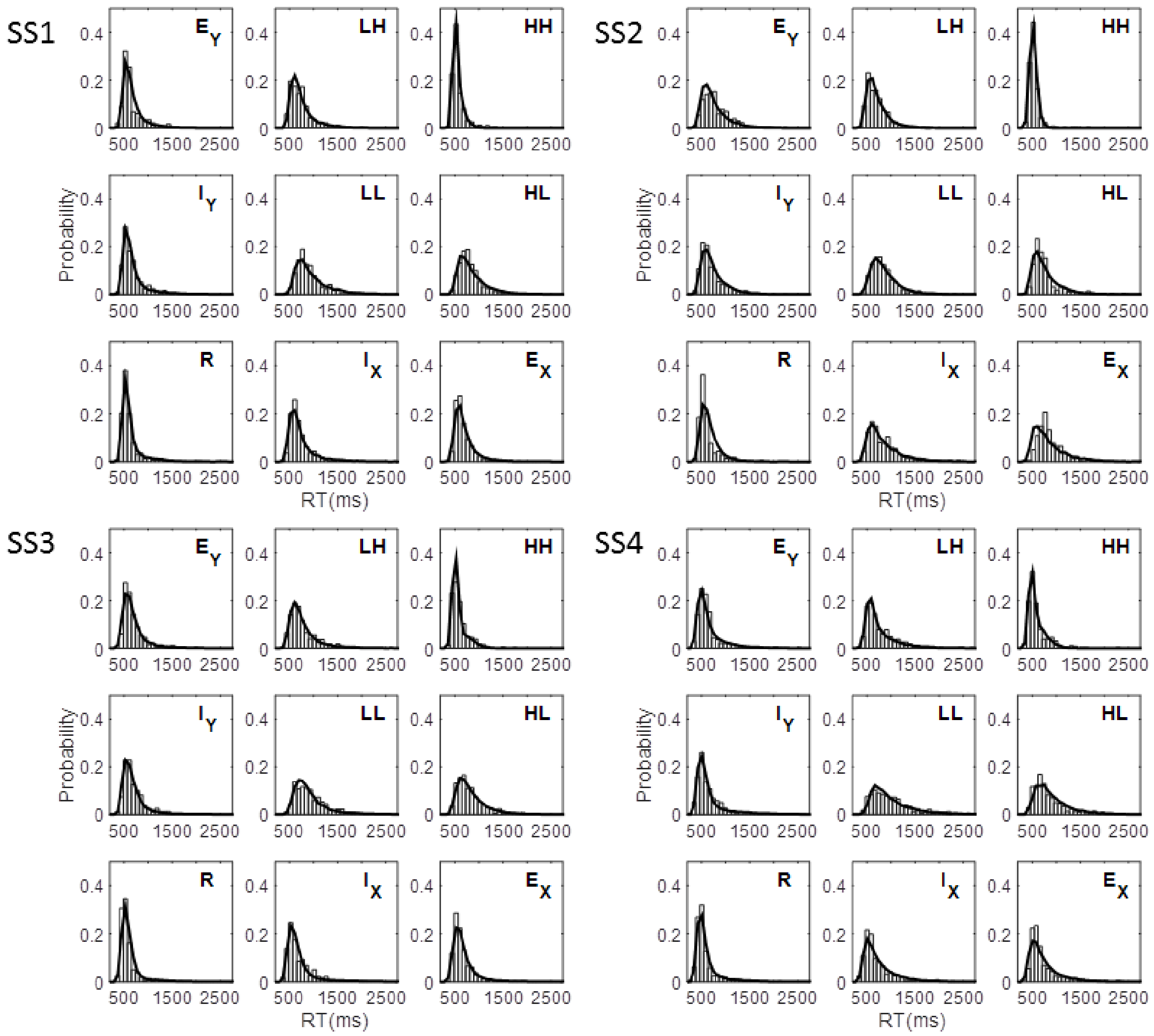

Figure S6. Fit (solid line) of the mixed serial-parallel self-terminating model to the response time (RT) distribution data (open bars) of the individual subjects in in the Size & Saturation condition (SS). (The fits of the parallel self-terminating model are presented for participant SS2). Each cell of each panel shows the RT distribution associated with an individual stimulus. Within each panel, the spatial layout of the stimuli is the same as in Figure 2. Stimuli are coded as high (H) and low (L) discriminability items (target category; A) as well as internal (I), external (E), and redundant (R), stimuli (contrast category; B).

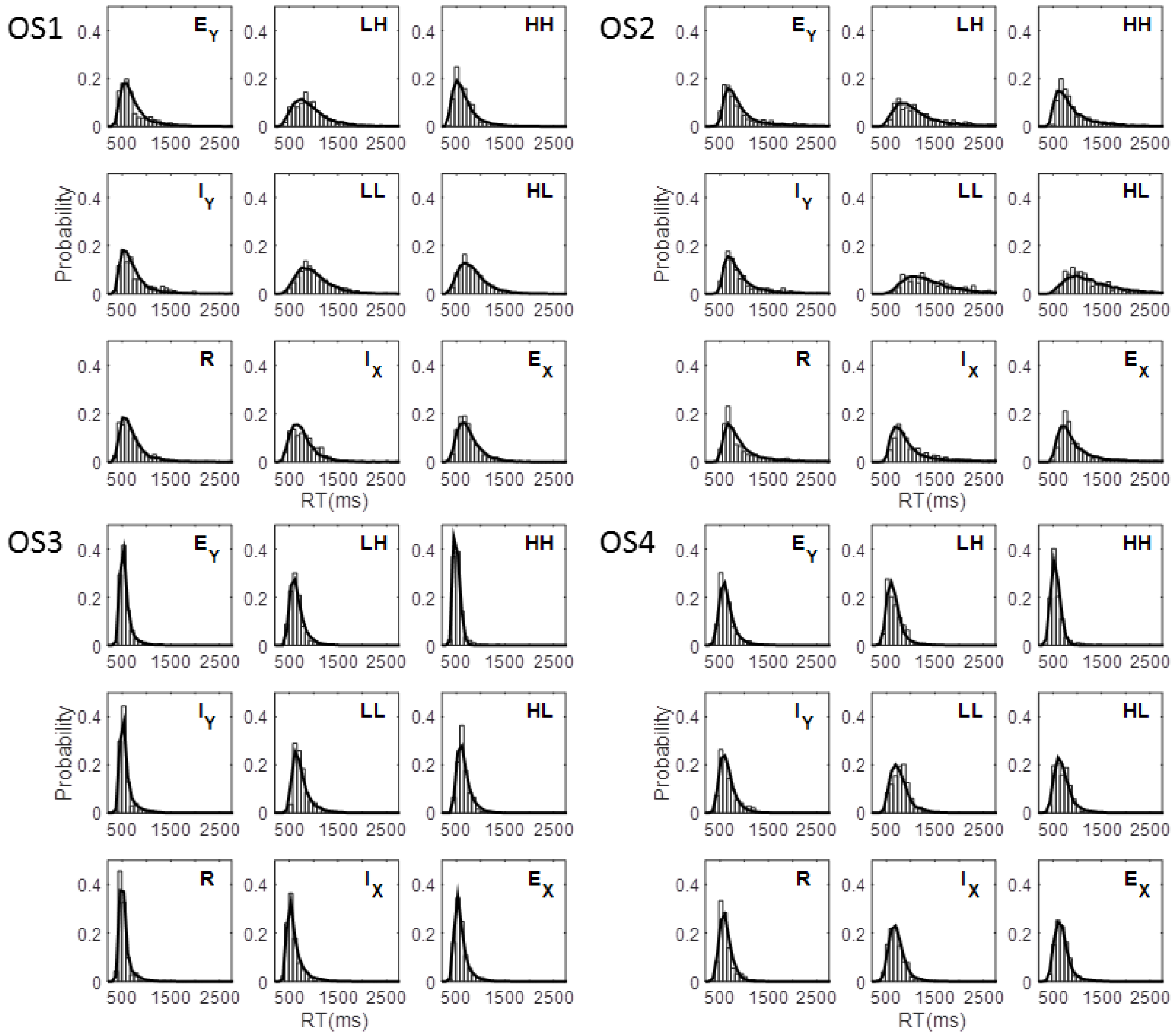

Figure S7. Fit (solid line) of the mixed serial-parallel self-terminating model to the response time (RT) distribution data (open bars) of the individual subjects in in the Orientation & Size condition (OS). Each cell of each panel shows the RT distribution associated with an individual stimulus. Within each panel, the spatial layout of the stimuli is the same as in Figure 2. Stimuli are coded as high (H) and low (L) discriminability items (target category; A) as well as internal (I), external (E), and redundant (R), stimuli (contrast category; B).

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