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A Parallel Distributed Processing Model of Stimulus–Stimulus and Stimulus–Response Compatibility

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A parallel distributed processing (PDP) model is proposed to account for choice reaction time (RT) performance in diverse cognitive and perceptual tasks such as the Stroop task, the Simon task, the Eriksen flanker task, and the stimulus–response compatibility task that are interrelated in terms of stimulus–stimulus and stimulus–response overlap (Kornblum, 1992). In multilayered (input–intermediate–output) networks, neuron-like nodes that represent stimulus and response features are grouped into mutually inhibitory modules that represent stimulus and response dimensions. The stimulus–stimulus overlap is implemented by a convergence of two input modules onto a common intermediate module, and the stimulus–response overlap by direct pathways representing automatic priming of outputs. Mean RTs are simulated in various simple tasks and, furthermore, predictions are generated for complex tasks based on performance in simpler tasks. The match between simulated and experimental results lends strong support for our PDP model of compatibility.

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Certain arrangements between stimuli and responses lead to faster and more accurate performance than others. In the Stroop task (Stroop, 1935/1992), where subjects are shown color words printed in colors and are instructed to name the colors, choice reaction time (RT) is faster when the color and color word are compatible rather than incompatible (Glaser & Glaser, 1982; MacLeod, 1991). In stimulus–response (SR) compatibility tasks (Fitts & Deininger, 1954; Fitts & Seeger, 1953) in which, for example, subjects are shown spatial stimuli and instructed to make spatial responses, RT is faster when the stimulus and response are compatible rather than incompatible (Duncan, 1977; Hommel & Prinz, 1997; Proctor & Reeve, 1990). In the Simon task (Simon, 1969, 1990), in which subjects are presented tones in the left or right ear and instructed to press a left or right key based on the pitch of the tone, RT is faster when the tone and the key are compatible in sides rather than incompatible. In the Eriksen flanker task (Eriksen & Eriksen, 1974; Eriksen & Schultz, 1979), where subjects are shown a letter string and instructed to press a key based on the central letter, RT is faster when the central letter and the flanking letters are compatible rather than incompatible. Despite the overwhelming similarity among these tasks and the existence of partial accounts for the Stroop task (e.g., Cohen, Dunbar, & McClelland, 1990; Cohen & Huston, 1994; Phaf, Van der Heijden, & Hudson, 1990), for SR compatibility and Simon tasks (John & Newell, 1990; Reeve & Proctor, 1990; Rosenbloom & Newell, 1987; Simon, 1969, 1990; Umilta & Nicoletti, 1992; Zorzi & Umilta, 1995), and for the Eriksen flanker task (Cohen, Servan-Schreiber, & McClelland, 1992; Eriksen & Schultz, 1979), these tasks are traditionally studied in isolation.

Recently, however, some researchers have begun to draw parallels between these tasks (e.g., Cohen et al., 1992; Kornblum, Hasbroucq, & Osman, 1990; Lu & Proctor, 1995). Kornblum and his colleagues (Kornblum, 1992, 1994; Kornblum et al., 1990; Kornblum & Lee, 1995) have proposed a dimensional overlap (DO) model to integrate these and other tasks under a systematic framework. According to this model, those tasks share two types of dimensional overlap, that is, stimulus–stimulus (SS) overlap—similarity between two stimulus dimensions, and SR overlap—similarity between a stimulus dimension and a response dimension. Importantly, this model makes ordinal predictions for performance in various tasks.

In this article, we take one further step in bringing these diverse cognitive and perceptual tasks together under a unified computational framework. Our goal is to integrate recent theoretical developments in two different research areas, the DO model in the study of compatibility and the parallel distributed processing (PDP) approach in computer modeling. We shall propose a PDP model of compatibility consisting of three-layered (input–intermediate–output) networks. At each layer are modules, each of which is used to represent a stimulus or response dimension (i.e., category). A module consists of multiple neuron-like nodes, each of which represents a stimulus or response feature. In the PDP networks, SS overlap is implemented by a convergence of two modules at the input layer onto a common module at the intermediate layer, and SR overlap by the presence of both automatic and controlled processes in the determination of responses (Kornblum et al., 1990). With such networks, we are able to simulate RTs in various tasks. In the remainder of this article, we shall first recapitulate the DO taxonomy of compatibility tasks (Kornblum, 1992, 1994) and summarize major findings in each of the tasks in the taxonomy. We shall then review the processing assumptions of Kornblum's (1992) DO model and Cohen et al.'s (1990) PDP model of Stroop effects. The bulk of this article consists of a description of representational and processing assumptions of our PDP model of compatibility and of the model's simulation of major results. Of special interest is our PDP model's ability to predict RT performance in one task from that in other tasks, which is taken as strong evidence supporting the PDP model. Finally, we compare our PDP model with other computational models of compatibility tasks.

DO TAXONOMY OF COMPATIBILITY TASKS AND SUMMARY OF MAJOR FINDINGS

The DO Taxonomy of Compatibility Tasks

In a typical reaction-time task, subjects are shown a stimulus and instructed to make a response. Both the stimulus and response may be multidimensional. Usually, only one stimulus dimension and one response dimension are designated as relevant, and subjects are instructed to pay attention to these. Other stimulus or response dimensions are irrelevant, and subjects are instructed to ignore these.

Two stimulus or response dimensions may be conceptually, perceptually, or structurally similar, and thus overlap (Kornblum et al., 1990). An overlap may occur between relevant stimulus and response dimensions (called *relevant SR overlap*), between irrelevant stimulus and response dimensions (called *irrelevant SR overlap*), or between two stimulus dimensions (called *SS overlap*). Although dimensional overlap is based on similarity and is, therefore, continuous in nature, for ease of exposition, in the taxonomy we treat it as discrete (present/absent) (however, it is treated as continuous in the PDP model proposed in this article). As is clear from Table 1, the DO taxonomy (Kornblum, 1992, 1994; Kornblum & Lee, 1995) systematically organizes many well-known tasks in the literature, including the ordinary SR compatibility task, the Simon task, the flanker task, and the Stroop task. In addition, the DO taxonomy includes novel tasks such as Ensemble 6. Note that according to Table 1, Ensembles 2, 3, and 4 are the constituents of Ensemble 8 (the Stroop task).

Particular instances of overlapping dimensions, as they occur in individual trials, either match or mismatch. Following the terminology in the SR com-

TABLE 1
A DO Taxonomy of Compatibility Tasks

	Type of dimensional overlap			Illustrative stimulus or response sets		
Ensemble	Relevant SR	Irrelevant SR	SS	Relevant S	Irrelevant S	Response
1	Absent	Absent	Absent	Colors	Positions	Digit names
2	Present	Absent	Absent	Colors	Digits	Color names
3	Absent	Present	Absent	Colors	Digits	Digit names
4	Absent	Absent	Present	Colors	Color words	Digit names
5	Present	Present	Absent	Colors	Positions	Colored key press
6	Present	Absent	Present	Positions	Colors and color words	Key press
7	Absent	Present	Present	Colors	Positions and color words	Key press
8	Present	Present	Present	Colors	Color words	Color names

Note. In the illustrative examples, positions refer to left/right positions, and key press refers to left/right key press.

patibility literature (e.g., Kornblum & Lee, 1995), matches and mismatches between the relevant stimulus and the response are called congruent or incongruent, respectively. Matches and mismatches between the irrelevant stimulus and the relevant stimulus or response are called SS- or SR-consistent and -inconsistent, respectively.[1]

Illustrative Examples and Major Findings

A variety of stimuli and responses has been used to produce various ensembles in the DO taxonomy. Here we provide illustrative examples with the following three sets of stimuli and responses that are common to all ensembles: (a) colors, color words, or color names, (b) digits or digit names, and (c) spatial positions of stimuli or responses. These sets of stimuli and responses should be distinguished as follows. First, they are different with respect to the presence or absence of dimensional overlap. The stimuli and responses from different sets are conceptually neutral to each other and thus do not overlap, but those from the same set are similar to each other and thus overlap. For example, whereas colors are conceptually neutral to and thus do not overlap with digits and spatial locations, they are similar to and thus overlap with color words and color names. Second, those sets of stimuli and responses are different with respect to carrier, which we define as the physical embodiment of stimuli and responses (e.g., using color or color word to embody the concept of color). For instance, a stimulus consisting of colors and color words is a mixed-carrier stimulus, but a stimulus consisting of two color patches is a single-carrier stimulus.

In Ensemble 1, none of the dimensions overlap. One example is a task (see Table 1) in which the stimuli are color patches (e.g., red and green) presented on the left or right of a fixation point, and the responses are digit names (e.g., ‘‘TWO’’ and ‘‘FOUR’’). Different SR mappings of the relevant stimuli (i.e., colors) onto the responses (i.e., digit names) yield identical RTs. Ensemble 1 is often incorporated as a neutral condition in studies of SR compatibility (Fitts & Deininger, 1954; Kornblum, 1994; Kornblum & Lee, 1995).

In Ensemble 2, the relevant stimulus and response dimensions overlap (relevant SR overlap). In the literature, it is known as the SR compatibility task (Fitts & Deininger, 1954; Fitts & Seeger, 1953; Hommel & Prinz, 1997; Proctor & Reeve, 1990). One example (see Table 1) is a task where subjects view digits written in color inks (e.g., red and green) and utter color names

[1] The terminology is different in the SR compatibility literature and the Stroop literature and in this article we have adopted the former terminology (see Kornblum & Lee, 1995, for a glossary). Note that in the Stroop literature (e.g., MacLeod, 1991) matches and mismatches between the relevant stimulus and the response are typically called compatible and incompatible, respectively, and matches and mismatches between the two stimuli are typically called SS-congruent and SS-incongruent, respectively.

(e.g., ''RED'' and ''GREEN'') based on the color of the inks. Because the relevant stimulus set, the color of the inks, overlaps with the response set, the color names, the stimuli may be mapped onto the responses congruently (e.g., red → ''RED'' and green → ''GREEN'') or incongruently (e.g., red → ''GREEN'' and green → ''RED''). The congruent SR mapping is faster and more accurate than the incongruent SR mapping (Duncan, 1977; Fitts & Deininger, 1954; Kornblum & Lee, 1995). The size of SR congruity effect is affected by a host of factors. For example, it is positively correlated with the number of stimuli and responses (Kornblum & Lee, 1995; Whitaker, 1979) and with the degree of dimensional overlap (Oliver & Kornblum, 1991; Wang & Proctor, 1996).

In Ensemble 3, the irrelevant stimulus dimension overlaps with the relevant response dimension (irrelevant SR overlap). In the literature, it is called the Simon task if the overlapping dimension is spatial (Hommel & Prinz, 1997; Lu & Proctor, 1995; Simon, 1969, 1990; Umilta & Nicoletti, 1992; Zorzi & Umilta, 1995). One example is a task (see Table 1) in which subjects see digits (e.g., 2 and 4) written in color inks and produce digit names (e.g., ''TWO'' and ''FOUR'') based on the colors. The irrelevant stimuli, the digits, may be consistent or inconsistent with the responses, the digit names. The SR-consistent condition is faster and more accurate than the SR-inconsistent condition (Kornblum & Lee, 1995; Simon, 1990).

In Ensemble 4, two stimulus dimensions overlap (SS overlap). One example is a task (see Table 1) in which subjects view color words (e.g., ''RED'' and ''GREEN'') written in color inks (e.g., red and green) and respond with digit names based on the color of the inks. The relevant stimuli (colors) and the irrelevant stimuli (color words) may be consistent or inconsistent with each other. The SS-consistent condition is faster than the SS-inconsistent condition (Kornblum, 1994; Zhang, 1996). Interestingly, when relevant and irrelevant stimuli are drawn from the same category (e.g., letters), the flanker task studied by Eriksen and his colleagues (Coles, Gratton, Bashore, Eriksen, & Donchin, 1985; Eriksen & Eriksen, 1974; Eriksen & Schultz, 1979; Gratton, Coles, Sirevaag, Eriksen, & Donchin, 1988) belongs to Ensemble 4 (see Kornblum, Stevens, Whipple, & Requin, in press). These researchers showed that with 2-to-1 mapping (e.g., mapping two stimuli to one response), RT is fastest when the relevant and irrelevant stimuli are identical (''identical'' condition), intermediate when they are assigned to the same response (''same response'' condition), slowest when they are assigned to different responses (''different response'' condition) (Eriksen & Eriksen, 1974; Eriksen & Schultz, 1979). The RT difference between the ''identical'' and ''same response'' conditions (approximately 10 ms) appears to demonstrate the effect of SS overlap and stimulus conflict, and the RT difference between the ''same response'' and ''different response'' conditions (approximately 20 ms) that of response competition.

In Ensemble 5, there exist two types of SR overlap: relevant and irrelevant.

A typical example is Hedge and Marsh's (1975) study (see Table 1), in which subjects saw a color light (e.g., red or green) on the left or right side and pressed a colored key (e.g., red or green) located on the left or right side. Note that this task deviates from the tradition of standard compatibility tasks and uses two-dimensional responses. For both the stimuli and responses, the relevant dimension was always color and the irrelevant dimension was always position. The color lights were mapped onto the colored keys either congruently (e.g., red → ''RED'' and green → ''GREEN'') or incongruently (e.g., red → ''GREEN'' and green → ''RED''). In two-choice tasks, RT was approximately 100 ms faster with congruent than with incongruent SR mapping (De Jong, Liang, & Lauber, 1994; Hedge & Marsh, 1975; Lu & Proctor, 1994; Simon, Sly, & Vilapakkam, 1981).

Irrespective of the SR mapping, the irrelevant stimulus and response dimensions—location—were consistent (e.g., both light and key on the left) or inconsistent (i.e., light on the left and response key on the right, or vice versa) with each other. With the congruent SR mapping, the SR-consistent condition was faster than the SR-inconsistent condition, which is in agreement with the results in Ensemble 3. However, with the incongruent SR mapping, the SR-consistent condition was slower than the SR-inconsistent condition (De Jong et al., 1994; Hedge & Marsh, 1975; Lu & Proctor, 1994; Simon et al., 1981). This finding is often referred to as the ''reverse Simon effect'' and has been the subject of considerable controversy (Barber, O'Leary, & Simon, 1994; De Jong et al., 1994; Guiard, Hasbroucq, & Possamai, 1994; Hasbroucq & Guiard, 1991; O'Leary, Barber, & Simon, 1994, 1995; Simon, 1990; Zhang & Kornblum, 1997).

In Ensemble 6, there are two types of overlap: relevant SR overlap and SS overlap. One example (see Table 1) is a task in which color words (e.g., ''RED'' and ''BLUE'') written in color inks (e.g., red and blue) are presented on either the left or right of a fixation point and subjects are instructed to press a left or right key based on the location of the stimulus (Zhang, Rozzi, & Ross, 1998). Note that this task deviates from the tradition of standard SR compatibility tasks since it uses one relevant and two irrelevant stimulus dimensions and the SS overlap is between the two irrelevant dimensions. Mean RT was approximately 50 ms (in two-choice tasks) or 120 ms (in three-choice tasks) faster for the congruent SR mapping (e.g., left → left and right → right) than for the incongruent SR mapping (e.g., left → right and right → left). However, no effect was found for the SS overlap between the two irrelevant stimuli, ink colors and color words; identical RTs were obtained in SS-consistent and SS-inconsistent conditions (Zhang et al., 1998).

In Ensemble 7, there are two types of overlap: irrelevant SR overlap and SS overlap. Similar to Ensemble 6, one relevant and two irrelevant stimulus dimensions are used. One example is a task (see Table 1) in which the stimuli consist of color words (e.g., ''RED'' and ''GREEN'') written in color inks (e.g., red and green) and displayed on the left or right. Subjects are instructed to press a left or right key based on the color of the inks. One irrelevant stimulus dimension, positions of the stimulus words, may be consistent (e.g., both on the left) or inconsistent (e.g., the stimulus on the left and the response on the right) with the responses, positions of the response keys. The other irrelevant stimulus dimension, the color words, may be consistent (e.g., the word ''RED'' written in red) or inconsistent (e.g., the word ''RED'' written in green) with the relevant stimuli, the colors of the inks. The SR-consistent conditions are faster and more accurate than the SR-inconsistent conditions (Kornblum, 1994; Simon & Berbaum, 1990; Stoffels & van der Molen, 1988). Similarly, SS-consistent conditions are faster and more accurate than SS-inconsistent conditions (Kornblum, 1994; Simon & Berbaum, 1990; Stoffels & van der Molen, 1988). In other words, the SR- and SS-consistent condition is always the fastest, SR- and SS-inconsistent condition is the slowest, and SR-consistent/SS-inconsistent and SR-inconsistent/SS-consistent conditions are in between.

In Ensemble 8, all three types of overlap are present. In the literature, this is known as the Stroop task (MacLeod, 1991; Stroop, 1935/1992). One example is a task (see Table 1) where color words (e.g., ''RED'' and ''GREEN'') are written in color inks (e.g., red and green) and subjects are instructed to produce color names (e.g., ''RED'' and ''GREEN'') based on the color of the inks. The relevant stimuli, the colors of the inks, may be mapped to the responses, the color names, either congruently (e.g., red → ''RED'' and green → ''GREEN'') or incongruently (e.g., red → ''GREEN'' and green → ''RED''). The congruent SR mapping is faster and more accurate than the incongruent SR mapping (Green & Barber, 1981; Kornblum, 1992; Simon & Sudalaimuthu, 1979; Zhang, 1996). The relevant stimuli, the colors of the inks, and the irrelevant stimuli, the color words, may be consistent (e.g., the word ''RED'' in red) or inconsistent (e.g., the word ''RED'' in green) with each other. The SS-consistent conditions are faster and more accurate than the SS-inconsistent conditions, in both congruent and incongruent SR mappings (Glaser & Glaser, 1982; Green & Barber, 1981; Lu & Proctor, 1994; Simon & Sudalaimuthu, 1979; Zhang, 1996). Note that in the incongruent SR mapping of 2-choice Stroop tasks, the SS-consistent condition is necessarily SR-inconsistent, and the SS-inconsistent condition is necessarily SR-consistent (Zhang & Kornblum, 1998). Thus, in the incongruent SR mapping, the effect of SR consistency appears to be reversed in a manner analogous to that in Ensemble 5; the SR-consistent condition is slower than the SR-inconsistent condition (Green & Barber, 1981; Lu & Proctor, 1994; Simon & Sudalaimuthu, 1979).

If subjects are shown color words written in ink colors and instructed to read the words instead of naming the ink colors, nearly identical RTs are obtained in SS-consistent and SS-inconsistent conditions (Glaser & Glaser, 1982). The lack of difference is often known as the absence of the reverse

Stroop effect. In other words, the Stroop effect is asymmetrical and whether or not the effect occurs depends upon response mode (i.e., whether it is naming the ink colors or reading the words).

In the Stroop tasks described above, the relevant and irrelevant stimuli are mixed in carrier—one is ink colors and the other is color words. Single-carrier Stroop tasks have also been studied (Glaser & Glaser, 1982, 1989; Zhang & Kornblum, 1998). Two versions of single-carrier conditions can be used. In the color/color version both stimuli are color patches, and in the word/word version both stimuli are color words. In both versions, different stimulus components are presented at separate locations and the relevant stimulus is identified by location. The Stroop effect is reported in both color/color and word/word versions (Glaser & Glaser, 1982; Zhang & Kornblum, 1998). The effect, however, is smaller in single-carrier conditions than that in mixed-carrier, color-naming conditions (Glaser & Glaser, 1982; Zhang, 1996; Zhang & Kornblum, 1998).

Relating Performance in Ensemble 8 with That in Ensembles 2, 3, and 4

Table 1 illustrates the fact that when stimuli and responses are balanced across conditions, Ensemble 8 is a composite of Ensembles 2, 3, and 4. Thus, the results in these tasks may be related. Zhang and Kornblum (1998) studied their relationships. In one experiment, Zhang and Kornblum (1998, Experiment 1) used single-carrier displays in which three stimulus words were presented one above the other (the middle word was relevant and the top and bottom words were irrelevant). Using color words and digit words as stimuli and color names and digit names as responses, they formed ensemble Types 2, 3, 4, and 8 while keeping stimuli and responses balanced across ensembles. As shown in Table 2, they obtained an SR congruity effect of 247 ms with Ensemble 2, an SR consistency effect of 35 ms with Ensemble 3, and an SS consistency effect of 31 ms with Ensemble 4. With congruent SR mapping in Ensemble 8, they obtained a Stroop effect of 23 ms (i.e., RT difference between SS/SR-consistent and SS/SR-inconsistent). Using four-choice tasks, Zhang and Kornblum (1998) produced a novel condition in the incongruent SR mapping: SS/SR-inconsistent (e.g., the relevant stimulus was the word ‘‘RED,’’ the irrelevant stimulus was the word ‘‘BLUE,’’ and the response was the word ‘‘GREEN’’). This condition is slower than SS-consistent/SR-inconsistent condition, which reveals an SS consistency effect in Ensemble 8. It is also slower than SR-consistent/SS-inconsistent condition, which reveals an SR consistency effect in Ensemble 8. Thus, the Stroop effect is attributed to both SS and SR consistency.

In a second experiment (Zhang & Kornblum, 1998, Experiment 2), color words were replaced by colors, and digit words by digits. Three stimulus components were arranged horizontally; the middle component was relevant and the left and right components were irrelevant. Again, Ensembles 2, 3,

TABLE 2
A Comparison of Mean RTs (ms) from Zhang and Kornblum (1998) with Simulation RTs

	Experimental		Simulation	
Condition	Exp. 1	Exp. 2	Exp. 1	Exp. 2
Ensemble 1		563		570
Ensemble 2, Congruent SR mapping	425	444	425	453
Ensemble 2, Incongruent SR mapping	672	663	675	668
Ensemble 3, SR-Consistent (SR^+)	590	536	575	533
Ensemble 3, SR-Inconsistent (SR^-)	625	573	625	573
Ensemble 4, SS-Consistent (SS^+)	594	571	595	545
Ensemble 4, SS-Inconsistent (SS^-)	625	597	625	575
Ensemble 8, Cong SR mapping, SS^+/SR^+	425	446	410	430
Ensemble 8, Cong SR mapping, SS^-/SR^-	448	471	430	453
Ensemble 8, Incong SR mapping, SS^+/SR^-	656	662	650	643
Ensemble 8, Incong SR mapping, SS^-/SR^+	679	684	665	668
Ensemble 8, Incong SR mapping, SS^-/SR^-	713	696	690	670

Note. Single-carrier stimuli are used in Ensemble 8. (+) indicates SR- or SS-consistent, and (−) indicates SR- or SS-inconsistent. Cong = Congruent; Incong = Incongruent; Exp. = Experiment.

4, and 8 were constructed. The experimental results are also shown in Table 2. As is clear in Table 2, the results from this experiment are nearly the same as in the first experiment.

Relating Performance in Ensemble 7 with That in Ensembles 3 and 4

Table 1 illustrates the fact that when stimuli and responses are balanced across conditions, Ensemble 7 is a composite of Ensembles 3 and 4. Kornblum (1994) compared performance in these ensembles. In all ensembles, subjects were instructed to press a left or right key based on the color (e.g., blue or green) of the stimulus. Note that the dimensions of the relevant stimulus (i.e., color) and of the response (i.e., key press) do not overlap. In Ensemble 3, the colors were presented in the left or right half of the rectangle, with the irrelevant, neutral words being presented at the center of the rectangle. In Ensemble 4, the colors were shown in the upper or lower half of the rectangle and thus did not overlap with the response, and the irrelevant color words (e.g., ‘‘BLUE’’ or ‘‘GREEN’’) were shown at the center of the rectangle. In Ensemble 7, the colors were displayed in the left or right half of the rectangle, and the irrelevant color words were shown at the center of the rectangle.

When the irrelevant stimuli were presented before the relevant stimulus with a stimulus-onset-asynchrony (SOA) of 200 ms, the SR consistency effect from Ensemble 3 was 32 ms and the SS consistency effect from Ensem-

TABLE 3
A Comparison of Mean RTs (ms) from Kornblum (1994, SOA = 200 ms) with Simulation RTs

Condition	Experimental	Simulation
Ensemble 3, SR-Consistent (SR^+)	378	405
Ensemble 3, SR-Inconsistent (SR^-)	410	430
Ensemble 4, SS-Consistent (SS^+)	373	375
Ensemble 4, SS-Inconsistent (SS^-)	421	440
Ensemble 7, SS^+/SR^+	370	360
Ensemble 7, SS^+/SR^-	390	375
Ensemble 7, SS^-/SR^+	422	415
Ensemble 7, SS^-/SR^-	440	445

ble 4 was 48 ms.[2] In Ensemble 7, the SR consistency effect was 19 ms and the SS consistency effect was 51 ms. The RT results are shown in Table 3.

PROCESSING ASSUMPTIONS OF THE DO MODEL

Kornblum (1992, 1994; Kornblum et al., 1990; Kornblum & Lee, 1995) put forward a stage model to account for RT differences in various ensembles included in Table 1. It comprises two major stages, a stimulus processing stage and a response production stage, separated by a discrete point. At the stimulus processing stage, all stimulus features are processed and stored in a stimulus vector, and the relevant stimulus is tagged. If two stimulus dimensions overlap (SS overlap), then two stimulus codes need to be compared, and any stimulus confusion needs to be cleared. As a result, RT ought to be slower if two stimulus features are inconsistent rather than consistent (SS consistency effect). This prediction is in accord with the major findings in Ensembles 4, 7, and 8.

At the response production stage, the correct response is identified through a controlled process and subsequently executed. The specific controlled process depends on dimensional overlap and the SR mapping instruction. If the SR mapping is congruent, it is assumed that subjects adopt a fast rule (e.g., the identity rule) to produce the correct response. Otherwise, subjects apply a slower rule (when it exists) or a memory search to arrive at the correct response. Response identification by the identity rule is the fastest, that by other rules (e.g., ‘‘+1 rule’’ or ‘‘−1 rule’’ with digit stimuli) is slower, and that by a memory search is the slowest (Schvaneveldt & Staudenmeyer, 1970). This introduces one source for the differential RTs between congruent and incongruent SR mapping conditions. Furthermore, when the stimulus

[2] We are mainly interested in the results at SOA = 200 ms because at SOA = 0 ms the SS consistency effect was nearly 0 ms (Kornblum, 1994), which would make computer simulations less meaningful.

overlaps with the response (relevant or irrelevant SR overlap), the presentation of a stimulus automatically activates its corresponding response. If the correct response and the automatically activated response are the same (as in the congruent SR mapping and in the SR-consistent condition), then it is executed quickly. If they are different (as in the incongruent SR mapping and in the SR-inconsistent condition), then the congruent or consistent response is aborted and the correct response is put in place and then executed. This abort process is time-consuming and leads to a slower RT in the incongruent and SR-inconsistent conditions than in the congruent and SR-consistent conditions. This introduces a second source for the differential RTs between congruent and incongruent SR mapping conditions. These two delays at the response production stage give rise to the effects of SR congruity and SR consistency in Ensembles 2, 3, 5, 6, 7, and 8.

Despite its broad scope, the DO model makes ordinal predictions only and as Cohen and Huston (1994) pointed out, it ‘‘requires quantification’’ (p. 473). In this article, we shall quantify the DO model by adopting the PDP approach. In the field of attention and performance, especially in the study of the Stroop effect, several PDP models have been proposed (Cohen et al., 1990; Cohen & Huston, 1994; Phaf et al., 1990). Next we review the PDP model of the Stroop effect proposed by Cohen et al. (1990).

THE COHEN ET AL. (1990) PDP MODEL OF THE STROOP EFFECT

The Cohen et al. (1990) PDP network of the Stroop effect was composed of two three-layer pathways—one pathway for ink colors and the other pathway for color words. Each pathway consisted of two input nodes (one node for the red stimulus and the other node for the green stimulus), two intermediate nodes, and two output nodes (one node for the ‘‘red’’ response and the other node for the ‘‘green’’ response). The two processing pathways converged onto the common nodes at the output layer.

The representation at the input and output layers was localist rather than distributed—each of the nodes at the input or output layer represented a particular stimulus or response feature (e.g., the ‘‘red’’ response). A node may take an activation value between 0 and 1. Information was strictly feedforward; nodes at the same layer were not connected, nor were there any feedback from later layers to earlier layers. Nodes at an early layer can send activation to nodes at the next layer via both positive and negative weights. In addition, there were two ‘‘task demand’’ nodes, one for the color naming task and the other for the word reading task, each of which sent positive activation to nodes at the intermediate layer in the corresponding pathway. That is, if the task was color naming, then the ‘‘task demand’’ node for color naming was turned on and sent positive activation to the color naming pathway; if the task was word reading, then the ‘‘task demand’’ node for word reading was turned on and sent positive activation to the word reading pathway.

Cohen et al.'s (1990) PDP network was trained to produce the correct response when information was presented in each of the two pathways. Cohen et al. (1990) used the backpropagation learning algorithm (Rumelhart, Hinton, & Williams, 1986) to adjust the connection weights. Basically, the learning algorithm was run iteratively to reduce the difference (or error) between the PDP network's output and the desired result. Because for adult subjects word reading was more highly practiced than color naming, Cohen et al. (1990) gave the network 5 times more training trials for word reading than for color naming (see Kanne, Balota, Spieler, & Faust, 1998, p. 176, for a replication and a correction). Consequently, stronger weights were produced in the word pathway for the connections between the input and intermediate layers and between the intermediate and output layers.

A simulation trial began by activating a task demand node for a particular task (e.g., for color naming) and allowing the activation of all nodes in the network to reach an asymptote. At this point, the intermediate nodes in the selected pathway and all the output nodes in the network were active (had an activation of 0.5) and the intermediate nodes in the unselected pathway were inactive. Then an input pattern (e.g., an SS-consistent pattern such as ''the word RED in a red color,'' or an SS-inconsistent pattern such as ''the word RED in a green color'') was given to the network, and all the nodes at both processing pathways were allowed to iterate continuously and in parallel until the activation accumulated from one of the output units exceeded the response threshold, which was set at 1.0. The number of iterations was recorded as the reaction time to that input. Cohen et al. (1990) added two random noises: one was added to the input of each node (except the input nodes) and the other to the response mechanism. Each of the two output nodes was associated with an evidence accumulator that added a random amount with a mean proportional to the activation difference between the output nodes. Because reaction times may vary in a network with noises, reaction times were averaged for a particular input pattern. Cohen et al. (1990) successfully simulated the major results in the congruent SR mapping of Ensemble 8 (Stroop tasks).

THE PDP MODEL OF COMPATIBILITY TASKS

Up to this point, there has been no single account that makes quantitative predictions for all 8 tasks included in the DO taxonomy in Table 1. Kornblum's (1992) DO model has a broad scope but does not make quantitative predictions, whereas Cohen et al.'s PDP model makes quantitative predictions but is restricted to the Stroop task. The aim of our modeling endeavor is to build upon these prior works and combine the strength of the DO model (e.g., broad scope) with the strength of the PDP approach (e.g., quantification under a continuous and parallel processing framework). We shall put forth a PDP model of compatibility tasks that can quantitatively account for the major findings in the various ensembles in the DO taxonomy (Table 1) with a common set of principles. According to the taxonomy (Table 1), Ensemble 1 is the baseline condition where no overlap is present, and it differs from Ensembles 2–8 only in terms of SS and SR overlap. Therefore, our strategy is to first represent Ensemble 1 in a three-layered connectionist network and then to specify the implementation of SS and SR overlap and the representation of Ensembles 2–8.

Our PDP model is based on, but goes beyond, the DO model (Kornblum, 1992, 1994; Kornblum et al., 1990; Kornblum & Lee, 1995). It retains the assumption that stimuli and responses are represented in terms of dimensions and features and that the concept of dimensional overlap is crucial. Furthermore, we stress the importance of the DO taxonomy (Table 1) in relating different tasks. It also retains the following processing assumptions of the DO model: (a) in the SS-inconsistent condition, stimulus conflict and confusion are produced as a result of SS overlap; (b) with relevant or irrelevant SR overlap, the response-overlapping stimulus leads to an automatic process, which primes a response that is congruent/consistent with the overlapping stimulus; and (c) the relevant stimulus leads to a controlled process, which prepares a correct response by applying an identity rule, a different rule, or a random search.

Moreover, our PDP model of compatibility explicates the representational and processing mechanisms in greater detail. We assume that a reaction time task is carried out through parallel processing at multiple (input–intermediate–output) layers. Information flows from the input end to the output end, and an earlier layer may continuously send partial activation to a later layer. Thus, unlike the DO model, the PDP model is not a discrete stage model. We also permit information transmission within the same layer. However, there is no feedback from a later layer to an earlier layer. Furthermore, we seek to implement our PDP model with a method of simple interaction and competition. The sole ‘‘currency’’ is the neuron-like activation and inhibition. Next, we state the representational and processing assumptions in detail.

Representational Assumptions

Stimuli and responses in reaction time tasks may be analyzed in terms of dimensions. In our PDP model, a stimulus or response dimension (e.g., colors) is represented by a module (Fig. 1), which consists of neuron-like nodes, each of which in turn represents a stimulus or response feature (e.g., a red color). The localist representation is used to keep our PDP model simple and it is similar to Cohen et al. (1990), McClelland (1992), and Phaf et al. (1990). The number of nodes within a given module is determined by the number of stimuli or responses within a dimension. In order to reflect the fact that at any given moment, a spatial location can only be occupied by

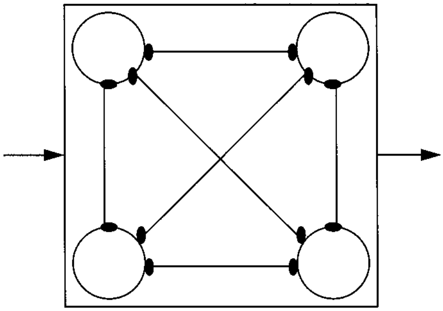


FIG. 1. A representative module (rectangle) composed of four mutually inhibitory nodes (circles). This module may be connected with other modules in an excitatory manner. Excitatory connections are represented by lines ending with an arrow and inhibitory connections by lines ending with a dot.

one object, for instance, an object cannot be both red and green, feature nodes within the same module are negatively connected and mutually inhibitory. Mutual inhibition allows nodes within the same module to compete against one another and the best fitting or strongest node will eventually win the competition.[3] Similar architecture has been employed to model letter recognition (McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982) and attention and human performance (Cohen & Huston, 1994; Cohen et al., 1992; McClelland, 1992; Phaf et al., 1990; Zorzi & Umilta, 1995).

Modules and nodes arranged in three layers (input, intermediate, and output) form the architectural building blocks of our PDP networks.[4] The input layer represents carrier-specific stimuli, for example, ink colors and color

[3] The use of mutual inhibition within a module deviates from the Cohen et al. (1990) network but agrees with other recent developments in the PDP modeling (e.g., Cohen, Usher, & McClelland, 1998; McClelland, 1992). In Cohen et al.'s (1990) network, there were between-layer inhibitions but no lateral inhibitions and as pointed out by Cohen et al. (1998, p. 192), such a network may create a problem; when partial activations of several alternatives are possible, there may be no net excitation of any alternatives. The problem can be solved by eliminating between-layer inhibitions and using within-module inhibitions (see Cohen et al., 1998).

[4] Like the Cohen et al. (1990) model of the Stroop effect, we adopt three-layer networks. Although two-layer networks can also model the Stroop effect (e.g., Cohen & Huston, 1994; Phaf et al., 1990), three-layer networks are computationally richer and more powerful (McClelland & Rumelhart, 1986, pp. 61–65). Three-layer networks are capable of implementing nonlinear decision surface for Boolean maps (e.g., the XOR problem, for which two-layer networks fail). Every continuous, finite mapping between input and output values can be approximated with arbitrary small error by a three-layer network (see Cybenko, 1989). The computational power and richness are important in modeling the wide variety of tasks in this article. In particular, the three-layer networks can simulate SS overlap with the connection between the first two layers and simulate SR overlap with the connection between the last two layers. They also allow us to separate the effects of stimulus processing from those of response production.

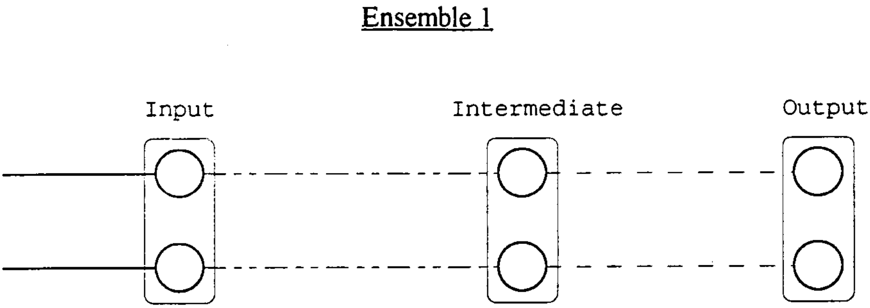


FIG. 2. A PDP network for Ensemble 1 composed of three modules (rectangles) with two nodes (circles) each. Within-module connections are analogous to those in Fig. 1 and therefore they are omitted here. For this and all subsequent figures, solid lines represent ‘‘task lines’’ in the relevant pathway, dash–dot lines represent ‘‘task lines’’ in the irrelevant pathway, dash–dot–dot lines represent ‘‘carrier lines,’’ dashed lines represent ‘‘control lines,’’ and dotted lines represent ‘‘automatic lines.’’ Note that only corresponding nodes in different modules are connected.

words. The intermediate layer represents abstract concepts, for example, color. The output layer represents responses, for example, color names. A simple PDP network for Ensemble 1 is shown in Fig. 2. Modules and nodes at the input layer receive their inputs from the external environment via ‘‘task lines,’’ which reflect attention allocated to different stimulus dimensions. Thus, the role of the task lines in our network is similar to that of the task demand nodes in the Cohen et al. (1990) network. The nodes at the input layer produce and send activation to corresponding nodes at the intermediate layer via ‘‘carrier lines,’’ which represent the strength between carrier-specific stimuli and their concepts. The nodes at the intermediate layer in turn produce and send activation to corresponding nodes at the output layer via ‘‘control lines’’ that represent SR mapping. The control lines implement the controlled process postulated in the DO model and reflect the SR mapping (Kornblum et al., 1990; Kornblum & Lee, 1995). Typically, the weight is set at 0.03 for ‘‘task lines,’’ 0.04 for ‘‘carrier lines,’’ and 0.03 for ‘‘control lines’’ (see Table 4).

Although our PDP model does not postulate separate, discrete stages for stimulus processing and response production, its stage-like architecture (i.e., input–intermediate–output layers; see Fig. 2) permits a consideration of separate contributions from stimulus conflict and response competition. Specifically, facilitation and inhibition at the input and intermediate layers appear to represent contributions of stimulus processing and those at the output layer appear to represent contributions of response competition.

Because stimuli and responses may be multidimensional, multiple modules may exist at each layer. Figure 3 shows a PDP network for Ensemble 4. In Fig. 3, the input layer contains two modules, one in the relevant pathway

TABLE 4
A List of Prototypical Parameter Values Used in the PDP Model

Parameter	Prototypical value	Experimental factors
Threshold	0.95 (fixed)	N and subjects
Decay	0.01 (fixed)	
b	5 (fixed)	
a	270	stimuli, responses, N, and subjects
Carrier lines	0.02 for ink color (fixed)	stimuli and subjects
	0.025 or 0.04 for other carriers	stimuli and subjects
Control lines	0.2 for congruent mapping	SR mapping, N, responses, and subjects
	0.03 for other mappings	SR mapping, N, responses, and subjects
Automatic lines	0.02	degree of dimensional overlap
Task lines	0.03 for relevant pathway (fixed)	attention and subjects
	0.011 for irrelevant pathway	attention and subjects
Mutual inhibition	from −0.02 to −0.025	stimulus category and subjects

Note. Prototypical parameter values are based on the simulation of Zhang and Kornblum's (1998, Experiment 1) results. For simulating the results in single-carrier conditions in Zhang and Kornblum (1998, Experiment 1), the weight for carrier lines was set at 0.04 and the weight for mutual inhibition was set at −0.025.

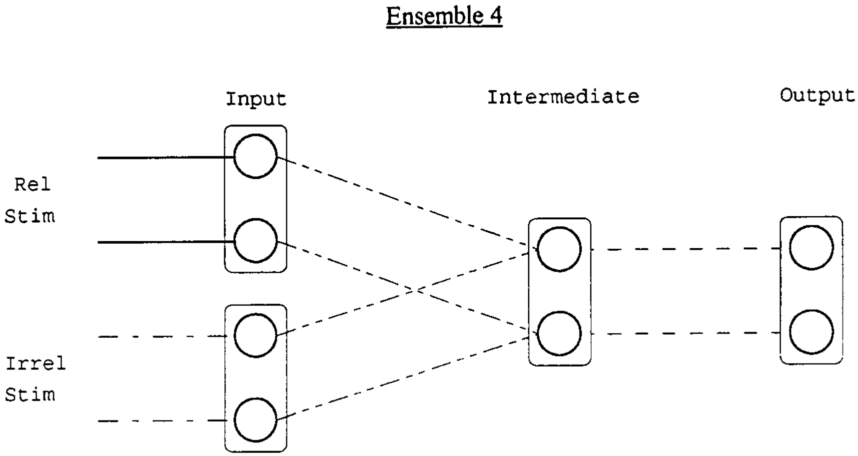


FIG. 3. A PDP network for Ensemble 4. In SS-consistent conditions external inputs may be 1 and 0 (weighted by task lines) for the feature nodes at the input layer in both the relevant and irrelevant pathways, and in SS-inconsistent conditions they may be 1 and 0 (weighted by task lines) in the relevant pathway and 0 and 1 (weighted by task lines) in the irrelevant pathway. See Fig. 2 for explanations of symbols.

and the other in the irrelevant pathway. Modules at the same layer are not connected, for they represent different categories. Because subjects are instructed to pay attention to the relevant stimulus and ignore the irrelevant stimulus, a larger weight is always assigned to the task lines in the relevant pathway and a smaller weight to those in the irrelevant pathway. Typically, the weight for task lines is set at 0.03 in the relevant pathway and 0.011 in the irrelevant pathway (see Table 4). For situations in which less attention is paid to the irrelevant stimulus, for example, when the irrelevant stimulus is spatially separated from the relevant stimulus or when the spatial separation between the stimulus components is increased, the weight for task lines in the irrelevant pathway is reduced accordingly.

With SS overlap (e.g., in Ensembles 4 and 8), we assume that two modules at the input layer converge onto a common module at the intermediate layer.[5] We further assume that the weight for carrier lines is dependent upon the association between carrier-specific features and their concepts only; a strong association is represented by large weights for carrier lines and a weak association by small weights. Note that the weights for carrier lines are independent of response mode (e.g., whether it is color naming or word reading). Because reading words is usually faster and more automatic than naming colors (Cattell, 1886; Posner & Snyder, 1975), in our simulations we assume larger weights (typically at 0.04; see Table 4) for carrier lines that represent color words and smaller weights (typically at 0.02; see Table 4) for carrier lines that represent ink colors. The use of differential weights for the color pathway and the word pathway is in accord with Cohen et al. (1990) and Cohen and Huston (1994).[6]

[5] It is well known that cortical regions such as V2 and V4 are crucial for color perception. If these regions are damaged, patients who previously had normal vision lose their ability to perceive and imagine colors. The color module at the input layer postulated in the PDP model might correspond to this region of the brain. Another region, the left posterior temporal and inferior parietal cortex, is critically involved in language and could be the site for the module of color words at the input layer postulated in the PDP model. Damasio and Damasio (1992) found that the regions for colors and language have projections to a common cortical region, the temporal segment of the left lingual gyrus. They found that although damage in the left lingual gyrus does not impair the patient's ability to perceive color or ability to speak, the patient's ability to put names to colors and to point to colors when given color names is severely impaired. We consider this anatomical finding in support of our assumption of convergence.

[6] Although both the Cohen et al. (1990) network and the present PDP network use stronger weights in the word pathway than in the color pathway, there is one difference between the two networks. In the Cohen et al. (1990) network, the color and word pathways converged at the output layer and stronger weights were used for the connections between the input and intermediate layers and between the intermediate and output layers. In the present PDP network for Ensembles 4 and 8, the color and word pathways converge at the intermediate layer (to represent SS overlap) and stronger weights are used only for the carrier lines connecting the input and intermediate layers. Despite the difference in implementational details, in both networks the use of differential weights for the color and word pathways is independent of response mode (e.g., whether the response is color naming or word reading).

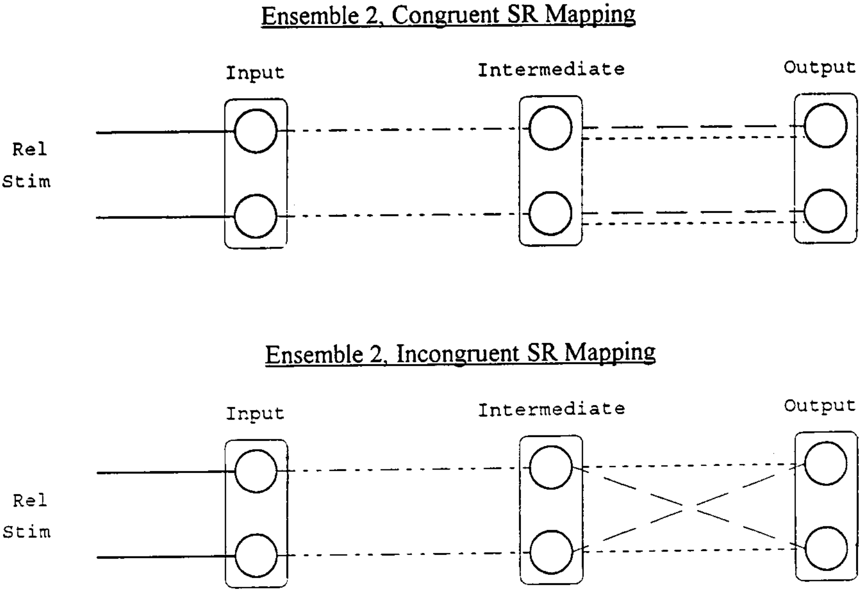


FIG. 4. The PDP networks for Ensemble 2, congruent SR mapping on the top and incongruent SR mapping at the bottom. See Fig. 2 for explanations of symbols.

Note that by converging two modules at the input layer to a common module at the intermediate layer and by using mutually inhibitory nodes within the module at the intermediate layer, we have implemented stimulus conflict (at the intermediate layer) in the SS-inconsistent condition of Ensemble 4 (Kornblum, 1992, 1994). Similarly, by using mutually inhibitory nodes within the module at the output layer, we have implemented response competition (at the output layer) in the SS-inconsistent condition of Ensemble 4 (Eriksen & Schultz, 1979). Thus, we have implemented both stimulus conflict and response competition in the Eriksen flanker task (see Coles et al., 1985; Gratton et al., 1988).

With SR overlap (e.g., in Ensemble 2), corresponding nodes at the intermediate and output layers are linked via ‘‘automatic lines,’’ which reflect the automatic priming. A PDP network for Ensemble 2 is shown in Fig. 4. The use of automatic lines implements the automatic process postulated in the DO model (Kornblum et al., 1990; Kornblum & Lee, 1995). It is consistent with the concept of spreading activation (Collins & Loftus, 1975) and the priming literature (Posner & Snyder, 1975). It has received direct experimental support (De Jong et al., 1994; Kornblum & Zhang, 1991) and the support of neurophysiological research (Coles, Gehring, Gratton, & Donchin, 1992; Eimer, 1995; Georgopoulos, Lurito, Petrides, Schwartz, & Massey, 1989). The weight for ‘‘automatic lines’’ is always smaller than that for ''control lines.'' It is typically set at 0.02 (see Table 4) and can vary with the degree of dimensional overlap; large SR overlap is indicated by a large weight, weak SR overlap by a small weight, and no overlap by a zero weight.

Note that in Fig. 4, the PDP networks for congruent and incongruent SR mappings are the same with the exception that the control lines join different nodes between intermediate and output layers. This difference, coupled with the fact that the automatic lines are the same for congruent and incongruent SR mappings, produces response competition in the incongruent mapping but not in the congruent mapping. Thus, consistent with the DO model (Kornblum, 1992; Kornblum et al., 1990) and the literature (e.g., Hommel & Prinz, 1997), we believe that response competition is responsible for the occurrence of SR compatibility. According to the DO model (Kornblum, 1992), in Ensembles 2, 5, 6, and 8, a fast rule is applied to produce the correct response in the congruent SR mapping whereas a slower rule or memory search is used in the incongruent SR mapping. Accordingly, in these ensembles, the weight for control lines is larger with the congruent SR mapping than with the incongruent SR mapping.[7] The weight is typically set at 0.2 for the congruent mapping and 0.03 for the incongruent mapping (see Table 4).

In Ensemble 3, the stimulus is two-dimensional and there is no SS overlap. So, both input and intermediate layers contain two modules, as shown in Fig. 5. In the relevant pathway, the feature nodes at intermediate and output layers are linked via control lines. Since the irrelevant stimulus dimension and the response dimension overlap (irrelevant SR overlap), corresponding nodes at the intermediate and output layers are linked via automatic lines. Note that competition can occur at the output layer but not in the input and intermediate layers. Thus, consistent with the DO model (Kornblum, 1992) and the literature (e.g., Lu & Proctor, 1995), we believe response competition is responsible for the occurrence of the Simon effect.

With the representational assumptions described above and the pattern of dimensional overlap shown in Table 1, we can readily create PDP networks for Ensembles 5–8 as shown in Figs. 6–9. Note that the architectural differences in the networks occur because of the presence or absence of various

[7] Following the DO model (Kornblum, 1992; Kornblum et al., 1990), there are two differences between the congruent and incongruent SR mappings. First, the control lines and automatic lines go to the same output nodes in the congruent SR mapping, but they go to different output nodes in the incongruent SR mapping. This introduces different RTs in the congruent and incongruent SR mappings. Second, since control lines in the present PDP model represent the response identification process in the DO model, which may deploy the fastest identity rule, a slower rule, or the slowest search (Schvaneveldt & Staudenmeyer, 1970), the weight for control lines must vary with the SR mapping in order to handle variable nonidentity mappings. The latter difference is crucial because the former difference alone is insufficient to explain the results such as Schvaneveldt and Staudenmeyer (1970).

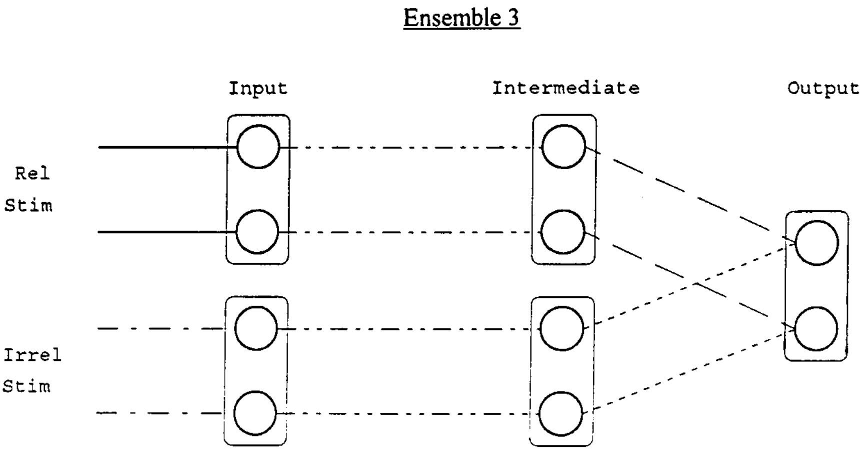


FIG. 5. A PDP network for Ensemble 3. In SR-consistent conditions external inputs may be 1 and 0 (weighted by task lines) for the feature nodes at the input layer in both the relevant and irrelevant pathways, and in SR-inconsistent conditions they may be 1 and 0 (weighted by task lines) in the relevant pathway and 0 and 1 (weighted by task lines) in the irrelevant pathway. See Fig. 2 for explanations of symbols.

types of overlap in different ensembles (see Table 1) and because of the use of different SR mapping instructions. The underlying principles used to construct the networks are common to all ensembles. For example, as in Ensemble 4, the SS overlap in Ensemble 8 is implemented by a convergence of two input modules onto the same intermediate module, and as in Ensembles 2 and 3, the SR overlap in Ensemble 8 is implemented by the automatic lines and response competition at the output layer.

Processing Assumptions

At any given moment in time, *t*, a node, *i*, is associated two values, an input value, $Input_i(t)$, which can be either positive or negative, and an activation value, $Activation_i(t)$, which is positive. Like a neuron, each feature node receives and integrates input and transforms the input to an activation, which is then sent to other feature nodes in the network. The total input to a node is determined by two factors: The first factor is its own activation at the preceding moment, $t - 1$, and the second factor is the weighted sum of outputs (i.e., activation) from connecting nodes. In other words, the input to node *i* at cycle *t* follows this input function,

$$Input_i(t) = (1 - Decay) \times Activation_i(t-1) + \sum_j W_{ji} \times Activation_j(t-1). \qquad (1)$$

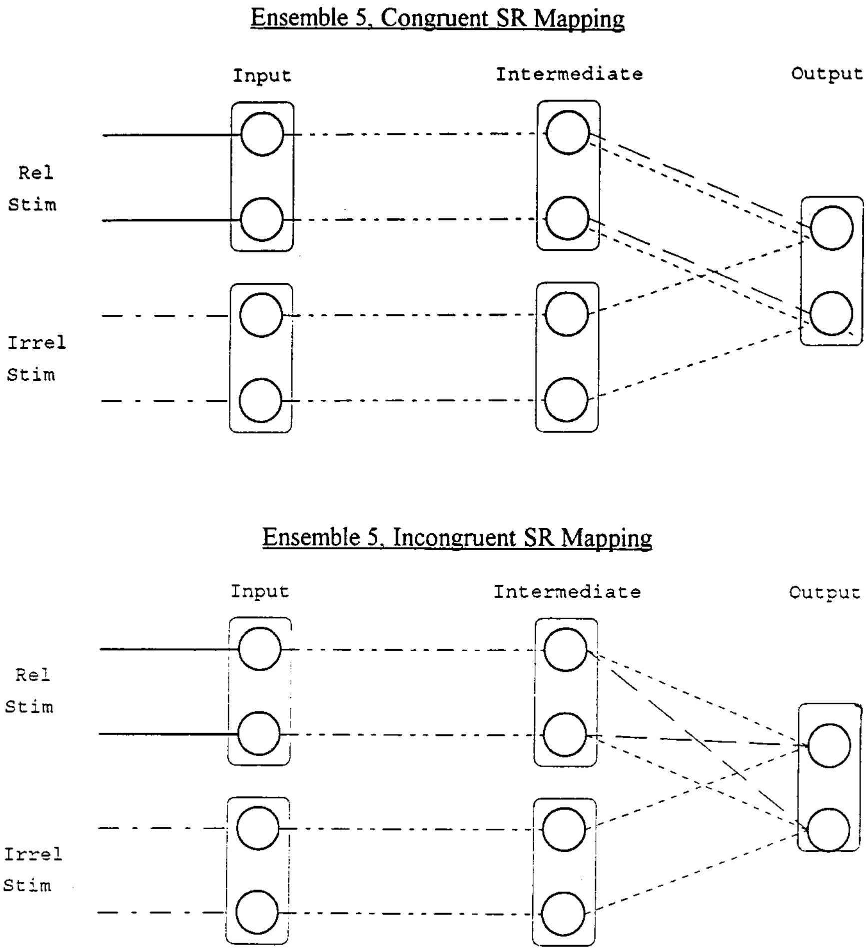
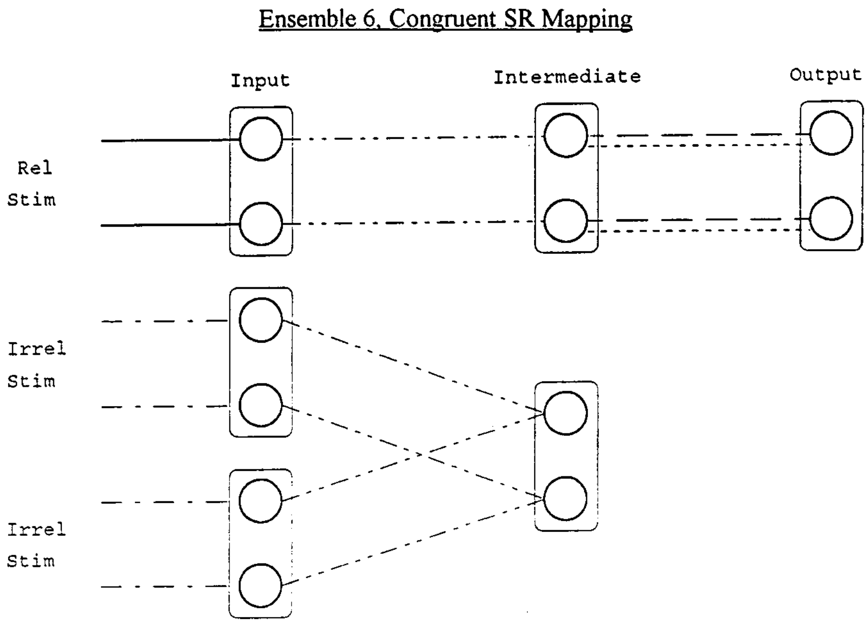


FIG. 6. The PDP networks for Ensemble 5, congruent SR mapping on the top and incongruent SR mapping at the bottom. See Fig. 2 for explanations of symbols.

The input is transformed to an activation with an activation function. This function is so chosen that the activation is (a) positive for all nodes at all the times and (b) a monotone increasing function of the input. For simplicity, a truncated [0, 1] linear function is employed, that is,

$$Activation_i(t) = \begin{cases} 1 & \text{if} \quad Input_i(t) \geq 1 \\ Input_i(t) & \text{if} \quad 0 < Input_i(t) < 1 \\ 0 & \text{if} \quad Input_i(t) \leq 0. \end{cases} \tag{2}$$



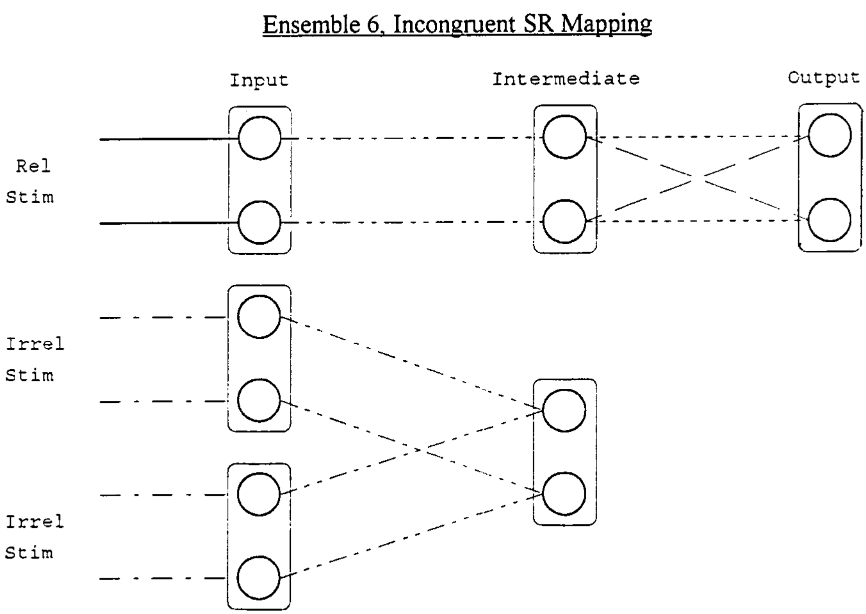


FIG. 7. The PDP networks for Ensemble 6, congruent SR mapping on the top and incongruent SR mapping at the bottom. See Fig. 2 for explanations of symbols.

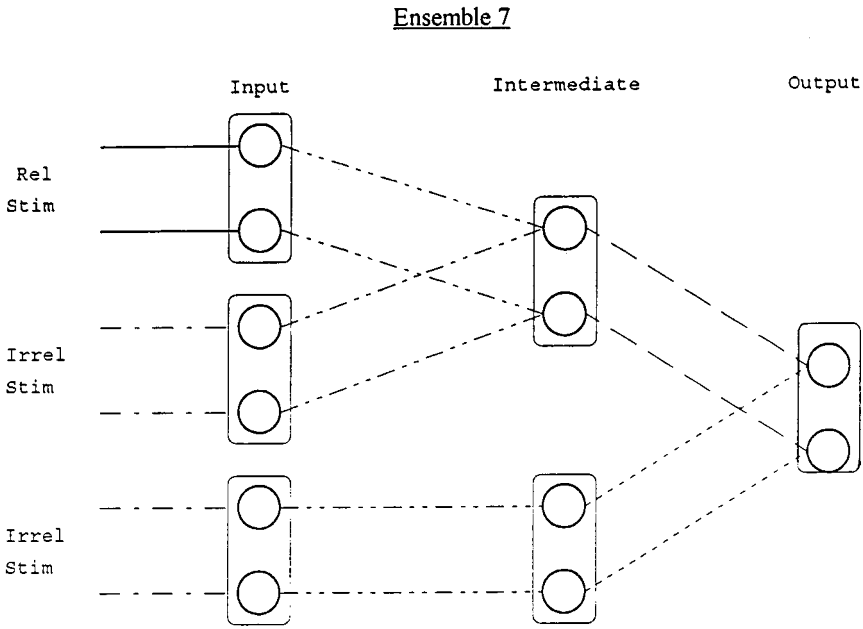


FIG. 8. A PDP network for Ensemble 7. In the ''SS/SR-consistent'' condition, external inputs may be 1 and 0 (weighted by task lines) for all pathways; in the ''SS-consistent/SR-inconsistent'' condition they may be 1 and 0 (weighted by task lines) for the relevant pathway and the first irrelevant pathway and 0 and 1 (weighted by task lines) for the second irrelevant pathway; in the ''SS-inconsistent/SR-consistent'' condition they may be 1 and 0 (weighted by task lines) for the relevant pathway and the second irrelevant pathway and 0 and 1 (weighted by task lines) for the first irrelevant pathway; and in the ''SS/SR-inconsistent'' condition they may be 1 and 0 (weighted by task lines) for the relevant pathway and 0 and 1 (weighted by task lines) for both irrelevant pathways. See Fig. 2 for explanations of symbols.

Input and Output Assumptions

We assume that if a stimulus feature is present, the corresponding node at the input layer receives an input of 1 weighted by task lines; otherwise, an input of 0. External input is assumed to be clamped to the PDP network and feeds a value of 1 or 0 (weighted by task lines) continuously to the feature nodes at the input layer. Unlike Cohen et al. (1990) and Cohen and Huston (1994) but similar to Zorzi and Umilta (1995), we do not add noise to the input and the model is therefore deterministic. So we simulate mean RTs only.

We further assume that once the activation of any nodes at the output layer reaches a response threshold, an overt response is executed. A similar assumption is made by Cohen et al. (1992) and Cohen and Huston (1994). Next, the number of simulation cycles and the response identity are recorded. The number of simulation cycles is converted to a simulated RT by the following linear function,

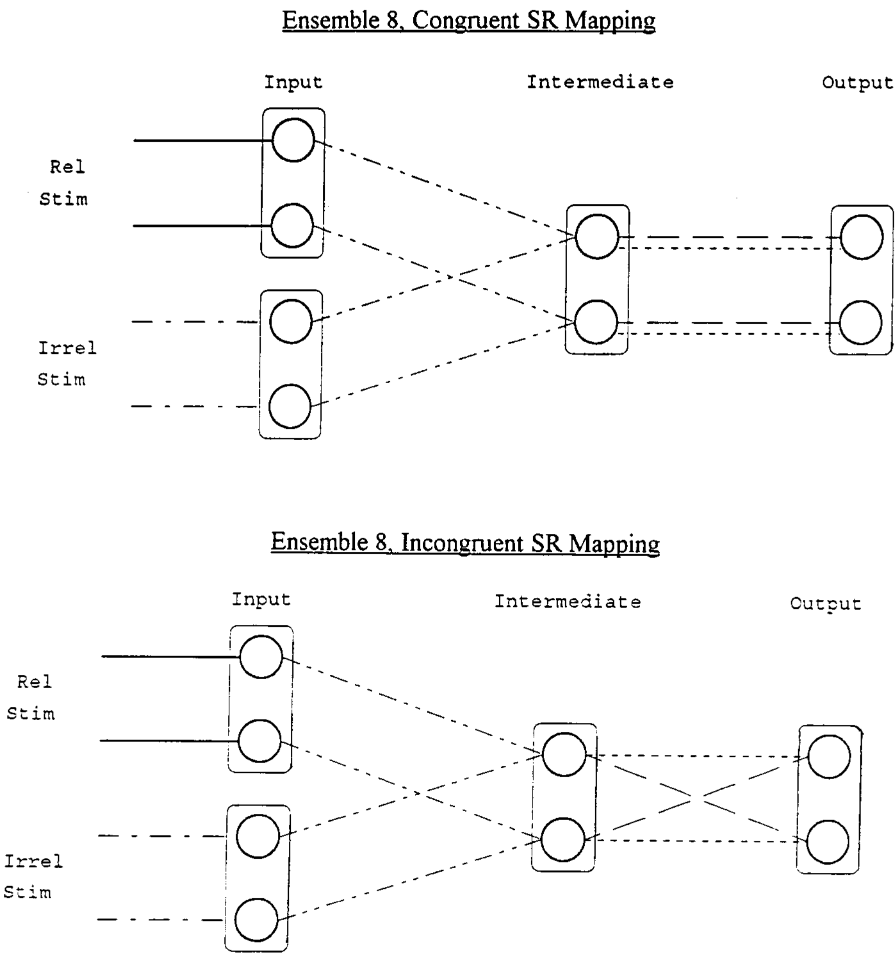


FIG. 9. The PDP networks for Ensemble 8, congruent SR mapping on the top and incongruent SR mapping at the bottom. In ''SS/SR-consistent'' and ''SS-consistent/SR-inconsistent'' conditions external inputs may be 1 and 0 (weighted by task lines) for both the relevant and irrelevant pathways, and in ''SS/SR-inconsistent'' and ''SS-inconsistent/SR-consistent'' conditions they may be 1 and 0 (weighted by task lines) for the relevant pathway and 0 and 1 (weighted by task lines) for the irrelevant pathway. See Fig. 2 for explanations of symbols.

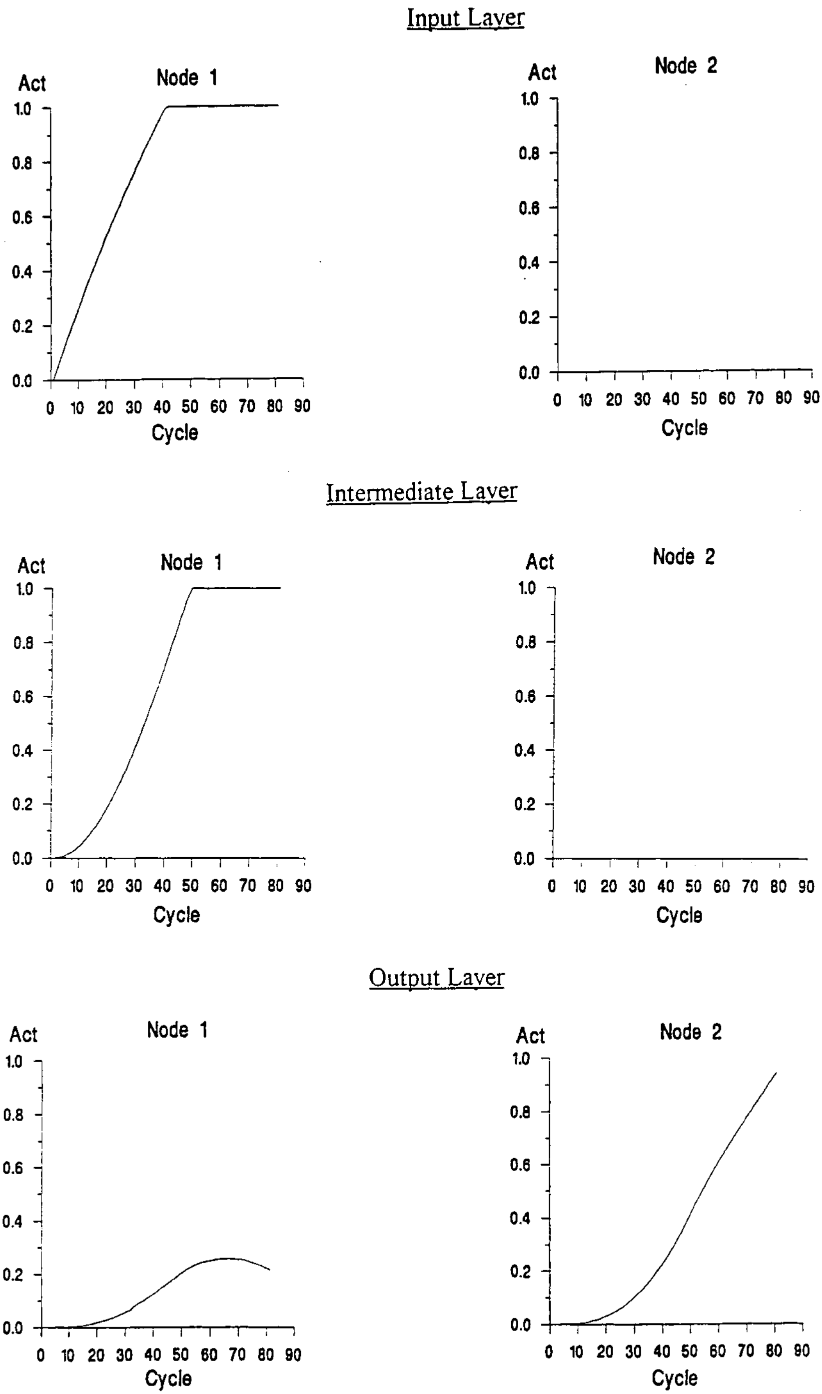
$$RT = a + bt, \tag{3}$$

where t is the number of cycles taken in the simulation, a is the amount of time that is supposedly unrelated to the response production and decision, for example, the time taken for perception, motor programming and execution, and b is a scale parameter converting simulation cycle to RT. For simulating the results of Zhang and Kornblum (1998, Experiment 1), a is set at 270 ms and b at 5 ms (see Table 4).

Operation of the PDP Model

With the parameter values listed in Table 4, the PDP networks are ready for simulation. We assume that at $t = 0$, all feature nodes in the network reach the quiescent state, and the activation is 0 for every node. At $t = 1$, external stimulation is turned on and stimulus information flows first to the corresponding nodes at the input layer, then to those at the intermediate layer, and finally to those at the output layer. All feature nodes in the PDP network update their inputs and activation in accordance with Eqs. (1) and (2) and move through successive cycles for successive rounds of updates. This updating process continues until the activation of one node at the output layer reaches the response threshold (set at 0.95, see Table 4). At this point, we consider that the network has made an overt response. A simulation trial is terminated and the number of simulation cycles and the response identity are recorded. The network is then reset for the next trial.

To reveal the inner working of the PDP model, we show in Fig. 10 the growth of activation as a function of simulation cycle with the incongruent SR mapping in Ensemble 2 (see Fig. 4 for the PDP network). In this simulation, two feature nodes are assumed for each module, and the parameters are set at the prototypical values tabulated in Table 4 (the weight for mutual inhibition is set at -0.025 and the weight for carrier lines is set at 0.04). At $t = 1$, external stimulation is given to node 1 at the input layer so its activation increases with time. Node 2 at the input layer does not receive external stimulation so it is not activated. Similarly, at the intermediate layer, node 1 increases its activation with t, whereas node 2 is not activated. At the output layer, both nodes 1 and 2 are activated. Because the weight for control lines is greater than that for automatic lines, node 2 is more activated than is node 1. Due to the mutual inhibition within the same module, these two nodes will compete and eventually node 1 is suppressed by node 2. At $t = 81$, node 2 is so activated that its activation reaches the response threshold. Thus, a response is made and the simulation trial ends. Interestingly, the activation of node 1 at the output layer shows an inverted U-shaped pattern. Recall that it reflects the time course of the automatic process. To study the automatic process empirically, Kornblum and Zhang (1991) used the response-signal procedure that required subjects to make a fast response upon the onset of a response signal (see Meyer, Irwin, Osman, & Kounios, 1988). When the time lag between the onset of the stimulus and the response signal was short, subjects often made incorrect responses. In the incongruent SR mapping of Ensemble 2, many of these incorrect responses were produced because of the occurrence of the automatic process. Kornblum and Zhang (1991) found an inverted U-shaped function for the time course of the auto-


Input Layer
Act
Node 1
1.0
0.8
0.6
0.4
0.2
0.0
0 10 20 30 40 50 60 70 80 90
Cycle
Act
Node 2
1.0
0.8
0.6
0.4
0.2
0.0
0 10 20 30 40 50 60 70 80 90
Cycle
Intermediate Layer
Act
Node 1
1.0
0.8
0.6
0.4
0.2
0.0
0 10 20 30 40 50 60 70 80 90
Cycle
Act
Node 2
1.0
0.8
0.6
0.4
0.2
0.0
0 10 20 30 40 50 60 70 80 90
Cycle
Output Layer
Act
Node 1
1.0
0.8
0.6
0.4
0.2
0.0
0 10 20 30 40 50 60 70 80 90
Cycle
Act
Node 2
1.0
0.8
0.6
0.4
0.2
0.0
0 10 20 30 40 50 60 70 80 90
Cycle

matic process. Note that both the empirical and the simulated time courses of the automatic process are inverted U-shaped functions.

SIMULATION

Parameter Estimations and Prototypical Values

The exact behavior of our PDP model is determined by approximately nine parameters (see Table 4). Since the PDP model is proposed to account for RTs in experiments that differ in terms of subjects, stimuli, responses, SR mapping, and the number of stimulus or response alternatives (N), it is unreasonable to expect constant parameter values across experiments. The use of constant parameter values would always produce a fixed set of RTs for each of the ensembles and therefore unnecessarily restrict the scope of the PDP model. Thus, similar to Cohen et al. (1990), Mozer (1991), and Phaf et al. (1990), parameter values are permitted to vary across experiments.

Note that the representational assumptions described previously have already provided constraints for the choice of parameter values. For example, the weight for ‘‘task lines’’ in the irrelevant pathway cannot exceed that in the relevant pathway, the weight for ‘‘carrier lines’’ is smaller for ink colors than for words, and the weight for ‘‘automatic lines’’ cannot exceed that for ‘‘control lines.’’ However, these constraints still leave many parameter values unspecified. Additional constraints may be furnished by design details and experimental data.

Without loss of generality, we fixed three parameter values—threshold, decay, and *b*—in all simulations (see Table 4). The remaining six parameter values can vary across experiments, but we established a set of prototypical values for them to be used in most of the simulations (in Table 4). These prototypical values are produced in simulating the results of Zhang and Kornblum (1998, Experiment 1). Zhang and Kornblum (1998, Experiment 1) used single-carrier conditions and had two conditions for Ensemble 2 (congruent and incongruent SR mappings), two conditions for Ensemble 3 (SR-consistent and -inconsistent), two conditions for Ensemble 4 (SS-consistent and -inconsistent), and five conditions for Ensemble 8. All six free parameters were allowed to vary in simulating the results and as a result, a set of best fitting parameter values was generated. These values were shown in Table 4 (the weight for mutual inhibition was set at -0.025 and the weight for carrier lines was set at 0.04) and were the prototypical values used in most of the simulations. Since a variety of experimental factors can influence

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FIG. 10. Activation as a function of simulation cycles for nodes at input (top panel), intermediate (middle panel), and output (bottom panel) layers for the incongruent SR mapping in Ensemble 2 (see the bottom panel of Fig. 4 for the PDP network).

the choice of parameter values (see Table 4), the exact parameter values used in each simulation may sometimes deviate from these typical values.

In the remainder of this simulation section, we first vary parameter values for four major parameters to simulate some basic phenomena. One major objective is to explore the relation between major parameters of our PDP model and corresponding psychological processes or experimental factors. Another objective is to better understand the model's behavior and provide additional constraints or a rationale for systematically varying major parameter values in later simulations. Next, we show that with a common set of parameter values, the PDP model can simulate the major results for each of the ensembles tabulated in Table 1 (with the exception of Ensemble 5). Then, we state how the PDP model predicts RT performance in complex ensembles (e.g., Ensembles 7 and 8) from that in simple ensembles (e.g., Ensembles 1, 2, 3, and 4).

Major Parameters and Corresponding Psychological Processes

Task lines. The relative weight for task lines in the relevant and irrelevant pathways can vary depending on the attention allocated to relevant and irrelevant stimuli. Reducing the weight in the irrelevant pathway while keeping that in the relevant pathway fixed leads to a smaller SR consistency effect in Ensemble 3 and a smaller SS consistency effect in Ensemble 4. This simulation indicates that SR and SS consistency effects are reduced when subjects pay less attention to the irrelevant stimulus, for example, when the relevant and irrelevant stimuli are spatially separated. Empirically, the SS consistency effect decreases when the spatial separation between the relevant and irrelevant stimuli is increased (Eriksen & Eriksen, 1974). Thus, the relative weight for task lines appears to modulate the size of SR and SS consistency effects.

Mutual inhibition. Mutual inhibition can occur at every layer and therefore it can modulate the contributions of stimulus conflict (in terms of inhibition at the input and intermediate layers) and response competition (in terms of inhibition at the output layer). Since both stimulus conflict and response competition can occur in Ensemble 4, we choose to vary the weight for mutual inhibition to examine its impact on the relative contributions of stimulus conflict and response competition. The 2-to-1 mapping is used. The network is the same as Fig. 3 except that there are four nodes in each of the input and intermediate modules and that two nodes at the intermediate layer are mapped onto one node at the output layer. When the weight for mutual inhibition is set at -0.025 and other parameters are set at the prototypical values in Table 4 (the weight for carrier lines is set 0.04), the simulated effect of stimulus conflict is 20 ms and that of response competition is 10 ms. When the weight for mutual inhibition is changed to -0.02, the simulated effect of stimulus conflict is 10 ms and that of response competition is 20 ms. Essentially, mutual inhibition within a module allows different alternatives (or nodes) to enter a competition and allows the best fitting alternative to

TABLE 5
Simulating Stroop Effects in Single- and Mixed-Carrier Stroop Tasks

Condition (Relevant/irrelevant)	Weight for carrier lines for: Relevant stimulus	Weight for carrier lines for: Irrelevant stimulus	Simulated effect (ms)
Color/Color	0.02	0.02	25
Word/Word	0.04	0.04	20
Color/Word	0.02	0.04	55
Word/Color	0.04	0.02	5

win the competition. The weight for mutual inhibition, along with the activation of the different nodes, determines the dynamics of the competition and the speed of winning the competition. In other words, mutual inhibition (and activation values for different alternatives) modulates the relative contributions of stimulus conflict and response competition.

Carrier lines and single- vs. mixed-carrier Stroop tasks. We employ the PDP network for the congruent SR mapping in Ensemble 8 (see Fig. 9) to simulate the Stroop results in both single- and mixed-carrier conditions. This can be successfully done with the prototypical parameter values listed in Table 4 (mutual inhibition is set at −0.025). As indicated in Tables 4 and 5, the weight for carrier lines should be different for ink colors and color words (also see Cohen et al., 1990; Cohen & Huston, 1994). In the color/color condition, the weight for carrier lines is set at 0.02 in both relevant and irrelevant pathways, and we simulated a Stroop effect of 25 ms. In the word/word condition, the weight for carrier lines is set at 0.04 in both pathways, and the simulated Stroop effect is 20 ms. These simulated RTs are shown in Table 5, and they are consistent with the results in single-carrier conditions reported by Zhang and Kornblum (1998).

In mixed-carrier conditions, if the irrelevant pathway has stronger carrier lines (as in color-naming version of the Stroop task or the color/word condition), the simulated Stroop effect is 55 ms. On the other hand, if the irrelevant pathway has weaker carrier lines (as in word-reading version of the Stroop task or the word/color condition), the simulated Stroop effect is 5 ms. The results are shown in Table 5. They are in agreement with experimental findings (e.g., Glaser & Glaser, 1982; Zhang, 1996). Note that the size of the Stroop effect depends on response mode (e.g., color naming vs. word reading). Note also that although the carrier lines appear to modulate the size of the Stroop effect (for similar conclusions, see Cohen et al., 1990; Cohen & Huston, 1994), in our PDP networks the weights for carrier lines are not varied as a function of response mode; regardless of response mode (color naming or word reading), the weight for carrier lines is 0.02 for the color pathway and 0.04 for the word pathway (see Table 5).

Automatic lines (SR overlap) and SR congruity effect. The size of SR congruity effect is also related to the degree of SR overlap (Oliver & Kornblum, 1991; Wang & Proctor, 1996). Oliver and Kornblum (1991) used three stimulus sets (digits: 1, 2, 3, and 4; letters: A, B, C, and D; and measures: inch, foot, yard, and mile) and three corresponding response sets and paired them to produce nine SR sets. With the paired comparison method, they derived a normalized measure of SR overlap, as shown in Fig. 11. For each of the nine SR sets, they produced a congruent SR mapping and an incongruent SR mapping and obtained SR congruity effects—RT differences between the congruent and incongruent SR mappings. Figure 11 also shows the normalized SR congruity effects. It is evident from Fig. 11 that the SR congruity effect correlates highly with SR overlap ($R^2 = 0.96$).

This positive correlation between SR overlap and SR congruity effect is readily simulated by the PDP model. Recall that the degree of SR overlap is represented in terms of the weight for automatic lines. For zero overlap the weight is 0 (lower limit). For complete overlap (100% overlap) the weight for automatic lines is similar to that for control lines in the incongruent SR mapping. This value is set at 0.027 (upper limit). For partial overlap, the weight for automatic lines is reduced proportionately. We set the weight for mutual inhibition at −0.02 and other parameters at the prototypical values listed in Table 4 (the weight for control lines is set at 0.03 and the weight for carrier lines is set at 0.04). The simulated SR congruity effects are normalized, as shown in Fig. 11. Clearly, the simulated and experimental SR congruity effects match well ($R^2 = 0.956$). Thus, the weight for automatic lines represents the degree of SR overlap and modulates the SR congruity effect.

Summary. To summarize, by varying four parameter values one at a time, we are able to simulate many phenomena in the literature. These simulations indicate that the major parameters in the PDP model are directly related to basic psychological processes and can be influenced by respective design factors. The relationships between the major parameters and experimental factors are specified in Table 4 and they provide further constraints on the choice of parameter values in later simulations.

Simulation of Major Results in 8 Ensembles

Ensemble 1. In Fig. 2, the first stimulus is mapped to the first response and the second stimulus to the second response. Of course, the opposite SR mapping can also be used. It is clear from Fig. 2 that simulated RT should be the same for different SR assignments. This is consistent with the major finding in this ensemble—the same RT for different SR assignments (e.g., Kornblum, 1994; Kornblum & Lee, 1995). With the prototypical parameter values listed in Table 4 (the weight for mutual inhibition is set at −0.025 and the weight for carrier lines is set at 0.04), the simulated RT was 620 ms.

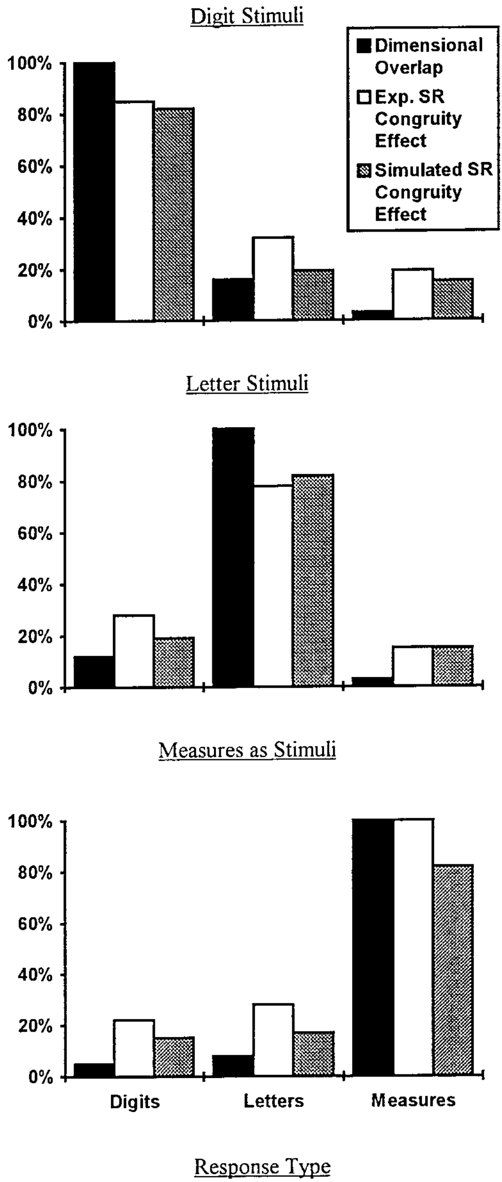


FIG. 11. Simulating the results of Oliver and Kornblum (1991). The top panel stands for digit stimuli, the middle panel for letter stimuli, and the bottom panel for measures as stimuli. Response labels are given on the abscissa. The dark bars stand for normalized indexes of dimensional overlap, the white bars stand for normalized SR congruity effects from the experiment, and the gray bars stand for normalized SR congruity effects from the simulation.

Ensembles 2 and 6. Since the simulation results are similar in these two ensembles, we will describe them together. It is clear from the PDP network for Ensemble 2 shown in Fig. 4 that so long as the weight for control lines is larger for the congruent SR mapping than for the incongruent SR mapping (this must hold for Ensemble 2 because according to the DO model a faster rule is used in the congruent SR mapping) and the weight for automatic lines is nonzero (this must hold for Ensemble 2 because a zero weight for automatic lines would constitute no dimensional overlap), simulated RT should always be faster in the congruent mapping than in the incongruent mapping (also see Footnote 7). With the prototypical parameter values in Table 4 (the weight for mutual inhibition is set at −0.025 and the weight for carrier lines is set at 0.04), we obtained 425 ms for the congruent SR mapping and 675 ms for the incongruent SR mapping.

The PDP networks for Ensemble 6 are illustrated in Fig. 7. Since the relevant SR overlap is present, the relevant stimuli can be mapped onto the responses either congruently or incongruently. With the PDP networks in Fig. 7 and the prototypical parameter values in Table 4 (the weight for mutual inhibition is set at −0.025 and the weight for carrier lines is set at 0.04), we simulated a faster RT (425 ms) in the congruent SR mapping than in the incongruent SR mapping (675 ms). The simulated SR congruity effect (250 ms) is larger than the empirical effect reported (Zhang et al., 1998). But recall that the typical values in Table 4 are based on four-choice tasks (Zhang & Kornblum, 1998) and the empirical data are from two-choice or three-choice tasks. Since in Zhang et al. (1998) the SR congruity effect was 50 ms in two-choice tasks but increased to 120 ms in three-choice tasks, the effect may be larger and close to the simulated result in four-choice tasks. In both SR mappings, two irrelevant stimulus features may be consistent or inconsistent with each other. Because the irrelevant stimuli are not connected to the output layer, it is clear that no difference is expected between SS-consistent and SS-inconsistent conditions. This is borne out by Zhang et al. (1998).

Ensemble 3. Ensemble 3 is similar to Ensemble 2 in that they both have an SR overlap. However, in Ensemble 3, the overlapping stimulus dimension is irrelevant. With the prototypical parameter values in Table 4 (the weight for mutual inhibition is set at −0.025 and the weight for carrier lines is set at 0.04) and the PDP network in Fig. 5, we obtained an SR consistency effect of 50 ms (RT is 575 ms in the SR-consistent condition and 625 ms in the SR-inconsistent condition). This simulation is consistent with the empirical data (e.g., Zhang & Kornblum, 1998). The size of this effect is contingent upon the choice of parameter values, in particular, the weight for automatic lines and task lines in the irrelevant pathway. Because the weight for task lines is smaller in the irrelevant pathway than in the relevant pathway, the simulated SR consistency effect in Ensemble 3 is always smaller than the simulated SR congruity effect in Ensemble 2. This is in accordance with the experimental findings (e.g., Kornblum & Lee, 1995).

Ensemble 4. With the PDP network in Fig. 3 and the prototypical parameter values in Table 4 (the weight for mutual inhibition is set at −0.025 and the weight for carrier lines is set at 0.04), we obtained an SS consistency effect of 30 ms (RT is 595 ms in the SS-consistent condition and 625 ms in the SS-inconsistent condition) for single-carrier conditions in Ensemble 4.[8] This is consistent with the experimental results (e.g., Kornblum, 1994; Zhang & Kornblum, 1998). Empirically, the SS consistency effect decreases when the relevant and irrelevant stimuli are spatially separated (Eriksen & Eriksen, 1974). In the simulation, a larger separation is represented by a smaller weight for task lines in the irrelevant pathway, which gives rise to a smaller simulated effect.

In 2-to-1 mapping, with the prototypical parameter values in Table 4 (the weight for mutual inhibition is set at −0.025 and weight for carrier lines is set at 0.04), we simulated the fastest RT for the ''identical'' condition (595 ms), an intermediate RT for the ''same response'' condition (615 ms), and the slowest RT for the ''different response'' condition (625 ms). If the weight for mutual inhibition is changed to −0.02, the simulated RT for the ''same response'' condition is 605 ms while that for the other conditions remains the same. The latter simulation demonstrates a small effect (10 ms) of stimulus conflict (i.e., RT difference between the ''identical'' and ''same response'' conditions) and a larger effect (20 ms) of response competition (i.e., RT difference between the ''same response'' and ''different response'' conditions). This simulated data pattern is in agreement with the experimental findings (e.g., Eriksen & Eriksen, 1974; Eriksen & Schultz, 1979).

Ensemble 5. With the PDP networks in Fig. 6 and the prototypical parameter values in Table 4 (the weight for mutual inhibition is set at −0.025 and the weight for carrier line is set at 0.02 for colors in the relevant pathway and 0.04 for positions in the irrelevant pathway), we simulated a faster RT (468 ms) in the congruent SR mapping than in the incongruent SR mapping (695 ms). The simulated SR congruity effect (227 ms) is larger than the empirical effect typically found (e.g., Hedge & Marsh, 1975), that is, approximately 100 ms. However, we need to remember that the prototypical values in the simulation are based on four-choice tasks (Zhang & Kornblum, 1998, Experiment 1) and the empirical data are based on two-choice tasks

[8] For simulating mixed-carrier conditions (i.e., color/word version) of Ensemble 4 with color as the relevant stimulus and color word as the irrelevant stimulus, we used the same unequal weights for carrier lines (0.02 for color and 0.04 for color word) as we had used in Ensemble 8. In addition, in order to simulate the fast key press responses in this Ensemble 4 task, we used large weights for the control lines. When the weight for the control lines was set at 0.3, 0.4, and 0.5, the simulated SS consistency effects were 45, 40, and 35 ms, respectively. These simulated effects were smaller than the Stroop effect in the mixed-carrier condition of Ensemble 8 (55 ms; see the color/word version in Table 5). In general, our model predicts that the SS consistency effect diminishes in size as the weight for control lines increases; this is because a faster RT allows the irrelevant stimulus to exert less influence.

(Hedge & Marsh, 1975). The SR congruity effect in four-choice tasks may be larger than 100 ms and close to the simulated result, for, as we have noted previously, SR congruity effect increases with the number of response alternatives.

In both SR mappings, we simulated a faster RT for the SR-consistent condition than for the SR-inconsistent condition. These simulation results are in agreement with the major findings except with the incongruent SR mapping (Hedge & Marsh, 1975; Lu & Proctor, 1994; Simon et al., 1981). As described previously, with the incongruent SR mapping, RTs are faster for the SR-inconsistent condition than for the SR-consistent condition.

Ensemble 7. With the network in Fig. 8 and the prototypical parameter values in Table 4 (the weight for mutual inhibition is set at −0.025 and the weight for carrier lines is set at 0.04), the simulated RT is 545 ms for the SR- and SS-consistent condition, 570 ms for SR-consistent/SS-inconsistent condition, 585 ms for SR-inconsistent/SS-consistent condition, and 625 ms for SR- and SS-inconsistent condition. This pattern of simulation results agrees with the experimental findings (Kornblum, 1994; Stoffels & van der Molen, 1988).

Ensemble 8. Figure 9 represents the PDP network for Ensemble 8. With this network and the prototypical parameter values shown in Table 4 (the weight for mutual inhibition is set at −0.025 and the weight for carrier lines is set at 0.04), we simulated the major results in this ensemble (see Table 2). Faster RTs are simulated for the congruent SR mapping than for the incongruent SR mapping. In the congruent SR mapping, we simulated faster RTs for the SS-consistent condition than for the SS-inconsistent condition. In the incongruent SR mapping, we simulated faster RTs for the SS-consistent/SR-inconsistent condition than for the SS-inconsistent/SR-consistent condition, which is in agreement with the dominance of SS consistency over SR consistency shown by Green and Barber (1981), Kornblum (1992), and Simon and Sudalaimuthu (1979). Note that the SS dominance is readily produced because we have implemented SS overlap in terms of the convergence of two input modules onto a common, intermediate module.

Note that according to the PDP model (Fig. 9), both stimulus conflict (in terms of convergence of relevant and irrelevant pathways and therefore inhibition at the intermediate layer) and response competition (in terms of mutual inhibition at the output layer) contribute to the Stroop effect. The same conclusion is also reached by Zhang and Kornblum (1998).

Predicting Complex Ensembles from Simpler Ensembles

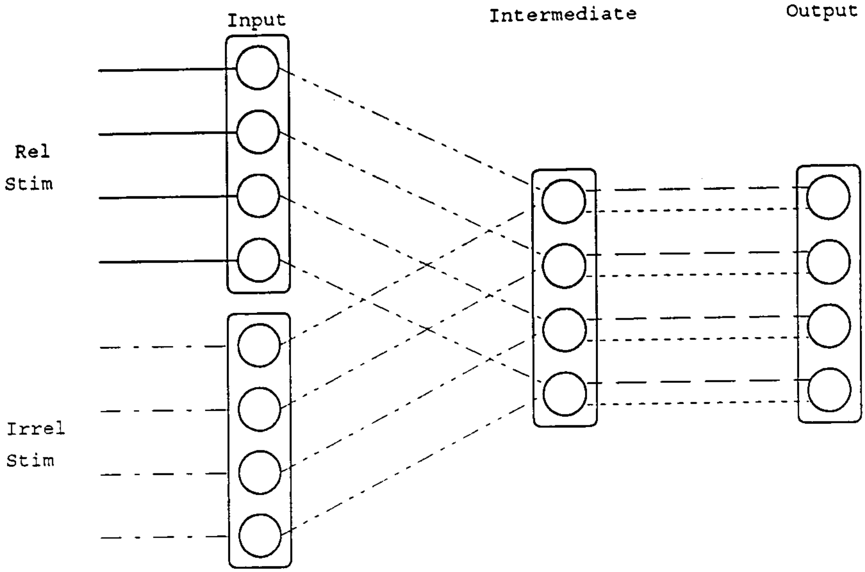
Below, our PDP model is made to predict RTs in Ensembles 7 and 8 based on RTs in simpler ensembles (e.g., Ensembles 1, 2, 3, and 4). Our strategy is to first utilize RTs in simpler ensembles as anchor points and force the PDP networks to simulate performance in them. Best-fitting parameter values are produced from this simulation. Then, these parameter values are kept constant and plugged in the PDP networks for complex ensembles. Predictions are then generated for Ensembles 7 and 8. The predicted RTs are compared to the experimental RTs to test the validity of the PDP model.

From Ensembles 2, 3, and 4 to Ensemble 8. Since we have represented SS and SR overlap in the same manner across Ensembles 2, 3, 4, and 8, the results in these ensembles should be correlated. In order to demonstrate that performance in Ensembles 2, 3, and 4 predicts performance in Ensemble 8 of Zhang and Kornblum's (1998) study, we generalized the PDP networks to handle four-choice tasks (see Fig. 12). First, we varied the parameter values in the PDP model to simulate their results in Ensembles 2, 3, and 4 (Zhang & Kornblum, 1998, Experiment 1), and obtained the prototypical parameter values as shown in Table 4 (the weight for mutual inhibition is set at −0.025 and the weight for carrier lines is set at 0.04). The results of simulation for Ensembles 2, 3, and 4 with the prototypical values are shown in Table 2. Next, our PDP model (Fig. 12) is used to make predictions for Ensemble 8. These predictions, also shown in Table 2, are a good match with the experimental results ($R^2 = 0.992$). Especially worth noting is that the PDP model attributes the Stroop effect to both stimulus conflict and response competition. Specifically, in the incongruent SR mapping, the RT difference between SS^+/SR^- and SS^-/SR^- illustrates the effect of stimulus conflict and the RT difference between SS^-/SR^+ and SS^-/SR^- illustrates the effect of response competition.

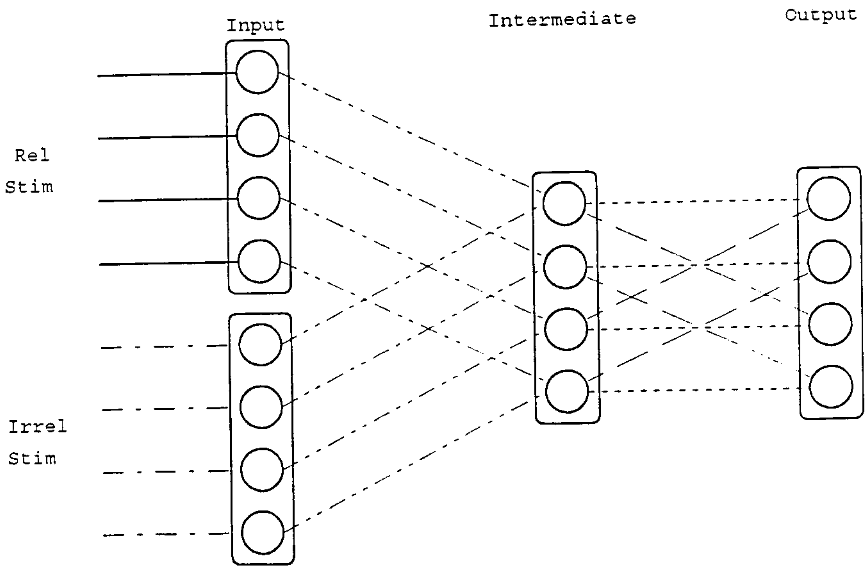
In simulating the results from a second experiment (Zhang & Kornblum, 1998, Experiment 2), we adopted the same two-step strategy. First, we simulated the data for Ensembles 1, 2, 3, and 4 (the weight for carrier lines was set at 0.02 for colors and 0.04 for digits). Even though we tried very hard to keep the same parameter values as those in Table 4, we needed to change a to 170 ms, the weight for task lines in the irrelevant pathway to 0.006, the weight for automatic lines to 0.024, and the weight for control lines in the congruent SR mapping to 0.04. These variations in parameter values are reasonable because Experiment 2 differed from Experiment 1 in terms of stimuli (both carrier and spatial separation) and subjects. With these parameter values, we simulated RT performance in Ensemble 8 (see Table 2). The simulated and empirical RTs match very well ($R^2 = 0.979$).

From Ensembles 3 and 4 to Ensemble 7. The PDP network in Fig. 8 is used to simulate SS and SR consistency effects in Ensembles 3, 4, and 7 (Kornblum, 1994, SOA = 200 ms). Since in Kornblum (1994) the relevant stimulus was ink color, the weight for carrier lines in the relevant pathway is set at 0.02; since the irrelevant stimulus was stimulus position or word, the weight for carrier lines in the irrelevant pathway is set at 0.025. Since there were two stimulus and response alternatives and the responses were key presses (which are usually faster) rather than vocal responses (which are usually slower), we increased the weight for control lines to 0.05 and set a at 85 ms. With the prototypical values listed in Table 4 for other parameters (mutual inhibition is set at −0.025), we first simulated RTs in Ensembles 3 and 4, as shown in Table 3. Note that while empirical and simulation RTs

Ensemble 8, Congruent SR Mapping



Ensemble 8, Incongruent SR Mapping



match well in Ensemble 4, the match is not as good in Ensemble 3. Without changing other parameter values, we found it difficult to obtain closer fit for both ensembles simultaneously. With the parameter values described above, we obtained the simulated RTs for Ensemble 7 shown in Table 3. The match between the empirical and simulation RTs is reasonable ($R^2 = 0.777$), but is not as good as that in Ensemble 8.

Summary. The PDP model of compatibility appears capable of predicting RTs in Ensembles 7 and 8 from RTs in Ensembles 2, 3, and 4. The model is used to simulate a total of 31 data points from three experiments (8 data points from Kornblum, 1994, and 11 and 12 data points from Zhang & Kornblum, 1998, Experiments 1 and 2, respectively). The degree of freedom in the simulation is considerably smaller; only 6 parameter values are varied. Overall, the simulated results match the empirical results reported in Zhang and Kornblum (1998, Experiments 1 and 2) and Kornblum (1994, SOA = 200 ms) very well (overall $R^2 = 0.987$ for the combined data).

Summary of Simulation Results: Capabilities and Limitations of the PDP Model of Compatibility

We have demonstrated the PDP model's capability to simulate many psychological phenomena. First, we have shown that the model's major parameters are related to basic psychological processes. Many important phenomena can be simulated by systematically varying just one parameter. Second, with the exception of the incongruent SR mapping in Ensemble 5, the PDP model simulated the major results in various ensembles listed in Table 1. Third, it appeared capable of predicting performance in complex ensembles such as Ensembles 7 and 8 from that in simpler ensembles (e.g., Ensembles 1, 2, 3, and 4).

Note that the PDP model in the present form does not capture the reverse Simon effect with the incongruent SR mapping in Ensemble 5. Currently, there are three proposals for the reverse Simon effect, one based on the notion of logical recoding (Hedge & Marsh, 1975), another based on the concept of display-control arrangement correspondence (Simon, 1990; Simon et al., 1981), and the third based on the concept of stimulus congruity (Guiard et al., 1994; Hasbroucq & Guiard, 1991). Hedge and Marsh (1975) argued that the relevant and irrelevant features of the stimulus are related to their respec-

FIG. 12. The PDP networks for four-choice Stroop tasks, congruent SR mapping on the top and incongruent SR mapping at the bottom. In ''SS/SR-consistent'' and ''SS-consistent/SR-inconsistent'' conditions external inputs may be 1, 0, 0, and 0 (weighted by task lines) for both the relevant and irrelevant pathways; in the ''SS-inconsistent/SR-consistent'' condition they may be 1, 0, 0, and 0 (weighted by task lines) for the relevant pathway and 0, 0, 1, and 0 (weighted by task lines) for the irrelevant pathway; and in ''SS/SR-inconsistent'' condition they may be 1, 0, 0, and 0 (weighted by task lines) for the relevant pathway and 0, 1, 0, and 0 (weighted by task lines) for the irrelevant pathway.

tive features of the correct response in terms of a logical recoding rule (‘‘same’’ or ‘‘reversal’’) and RT is faster when the recodings of the relevant and irrelevant stimuli are of the same type (e.g., ‘‘reversal rule’’ for both) than when they are of different types (e.g., ‘‘same rule’’ for one and ‘‘reversal rule’’ for the other). Simon (1990; Simon, Sly, & Vilapakkam, 1981) defined display control arrangement correspondence as the correspondence or noncorrespondence of the location of the color stimulus with the location of the response key of the same color and argued that RT is faster when display control arrangement correspondence is consistent than when it is inconsistent. Hasbroucq and Guiard (1991) reasoned that since in Hedge and Marsh (1975) color and location were perfectly correlated in the responses, subjects could also associate color and location of the stimulus in a similar manner and therefore lead to stimulus congruity or incongruity. They argued that RT is faster when there is stimulus congruity than when there is stimulus incongruity.

If any one of these proposals is added to our model, the PDP model should be able to produce the reverse Simon effect. For example, if we would implement the concept of stimulus congruity in the same manner as SS overlap (as in Ensemble 8) and add lateral inhibition between the two modules at the intermediate layer (see Fig. 6), the network for Ensemble 5 would become nearly indistinguishable from that for Ensemble 8 (Fig. 9). Consequently, we would be able to simulate SS dominance in Ensemble 5, for, as noted previously, SS dominance is readily simulated in Ensemble 8 (because of SS overlap). However, we choose not to implement these proposals on an ad hoc basis because at this point there has been little consensus on this issue (Barber et al., 1994; De Jong et al., 1994; Guiard et al., 1994; Lu & Proctor, 1995; O’Leary et al., 1994, 1995; Zhang & Kornblum, 1997).

RELATIONS TO OTHER COMPUTATIONAL MODELS OF COMPATIBILITY TASKS

There exist several computational models of compatibility tasks. Below, we discuss our PDP model’s relations to these other models. Because the previous models are restricted to one ensemble and our PDP model has a much broader scope (encompassing all 8 ensembles in Table 1), a complete comparison is not possible. Instead, direct comparisons are made mainly between the previous models and our PDP networks designed for the same tasks.

Connectionist Models of the Stroop Effect, the Flanker Effect, and the Simon Effect

As stated previously, Cohen et al. (1990) put forth a connectionist model of the Stroop effect. It consists of nodes at three layers: input, intermediate, and output. There are four input nodes, each representing a stimulus color (red or green) in the relevant or irrelevant pathway (for ink colors or color words). Input nodes send activation to four corresponding nodes at the intermediate layer, which in turn feed onto two output nodes, one for each response (‘‘RED’’ or ‘‘GREEN’’). An overt response is made when the difference between the cumulative activation of the two output nodes exceeds a threshold. The connection weights reflect the strength of the stimulus dimensions: The color word dimension is stronger than the ink color dimension. Moreover, two task demand nodes are implemented, one for color naming and the other for word reading. This model simulated both the presence of the Stroop effect and the absence of the reverse Stroop effect (Stroop, 1935/1992).

Recently, Cohen and Huston (1994) updated Cohen et al.’s (1990) original model. In Cohen and Huston’s (1994) GRAIN model of the Stroop task, nodes are mutually inhibitory and are organized into modules. In fact, their GRAIN model is bidirectional; excitatory information can flow from response nodes to stimulus nodes as well as from stimulus nodes to response nodes. An overt response is made when one of the output nodes exceeds a threshold. This updated GRAIN model (Cohen & Huston, 1994) accounts for the Stroop effect in a manner similar to that of Cohen et al. (1990).

As noted previously, our PDP model shares many commonalities with Cohen et al.’s (1990) and Cohen and Huston’s (1994) models. In general, all these models postulate the existence of multiple parallel pathways and these pathways converge to permit different sources of information to compete. Specifically, the task lines in our model are similar to the task demand nodes in Cohen et al.’s (1990) and Cohen and Huston’s (1994) models since both are used to specify the relevant and irrelevant stimuli. Our use of differential weights for carrier lines (e.g., smaller weight for ink colors than for color words) is similar to the adoption of smaller weight for the ink color dimension than for the color word dimension in Cohen et al.’s (1990) and Cohen and Huston’s models. In all these models, the differential weight is critical in simulating the presence of the Stroop effect (in color naming version) and the absence of the reverse Stroop effect (in word reading version).

Significant differences exist, however. First and foremost, Cohen et al.’s (1990) and Cohen and Huston’s (1994) models are restricted to the congruent SR mapping of the Stroop task only, but our model has a considerably broader scope. With the use of control lines, our model can handle both the congruent and incongruent SR mappings of the Stroop task. It can also handle other compatibility tasks included in the DO taxonomy (Table 1). With respect to the congruent SR mapping of the Stroop task, our model (see Fig. 9) is different from their models, especially Cohen et al.’s (1990) model. Our PDP model and Cohen and Huston’s (1994) GRAIN model assume that nodes are organized in terms of modules with mutually inhibitory nodes, whereas Cohen et al.’s (1990) model does not. In our PDP model and Cohen and Huston’s (1994) model a response occurs when the activation of any one of the output nodes exceeds the threshold, but in Cohen et al.'s (1990) model a response occurs when the difference between the activation of two output nodes exceeds the threshold. Furthermore, although in all these models different pathways eventually converge, the convergence occurs at the output layer in Cohen et al.'s (1990) and Cohen and Huston's (1994) models, but in our PDP model the convergence occurs at the intermediate layer. Our model assumes a common module at the intermediate layer for link colors and color words (with SS overlap) in the Stroop task (Ensemble 8) and Eriksen flanker task (Ensemble 4), whereas Cohen et al.'s (1990) model has separate nodes for ink colors and color words at the intermediate layer and Cohen and Huston's (1994) GRAIN model does not have an intermediate layer. Consequently, competition can occur at both intermediate and output layers in our PDP model, reflecting the contributions from both stimulus conflict and response competition (Zhang & Kornblum, 1998). In addition, while Cohen et al. (1990) and Cohen and Huston (1994) added noise in their models, our model has not. At present, our model always produces the correct response and is not equipped to simulate accuracy data. Also note that whereas Cohen et al.'s (1990) model provided an integrated account of learning and Stroop effects, neither Cohen and Huston's (1994) model nor our PDP model does. Instead, our PDP model has focused on the processing dynamics in different tasks.

Cohen et al. (1992) proposed an interactive activation model to account for results in the Eriksen flanker task. Their model is composed of three mutually inhibitory modules: input, output, and attention. The input module is made of six nodes representing two letters (H and S) at three spatial locations (left, middle, and right); the output module is made of two nodes representing two responses; and the attention module is made of three nodes representing three spatial locations (left, middle, and right). Cohen et al.'s (1992) model successfully simulated the SS consistency effect in the Eriksen flanker task, especially the results reported by Gratton et al. (1988).

Our PDP network for Ensemble 4 (see Fig. 3) shares similar features with Cohen et al.'s (1992) model. Both assume the existence of parallel pathways and competitive processing. In both models, different pathways eventually converge. Furthermore, our use of differential weights for task lines in the relevant and irrelevant pathways is similar to Cohen et al.'s (1992) adoption of the attention module. Although Cohen et al. (1992) did not use an intermediate layer, their input module seems to accomplish similar functions implemented by our input and intermediate layers. However, Cohen et al.'s (1992) model is intended for the Eriksen flanker task only, whereas our PDP model simulates all eight ensembles in Table 1 and implements networks for tasks other than Ensemble 4 (Fig. 3). Again, while Cohen et al. (1992) added noise in their model, our model has not.

Zorzi and Umilta (1995) have proposed a connectionist model of the Simon effect. Their model posits three modules with two nodes each. These modules represent responses, stimulus features, and stimulus positions, respectively. The two response nodes are mutually inhibitory with each other, whereas nodes representing stimulus features and positions are not. Furthermore, most of the connection weights in their model are modifiable with the Hebbian learning algorithm. With this architecture, they simulated the basic Simon effect.

Our PDP network for Ensemble 3 (Fig. 5) is similar to Zorzi and Umilta's (1995) model. Both models assume the occurrence of multiple pathways, which converge at the output layer. In both models, competitive processing occurs at the output layer. Both models assume that the irrelevant spatial code automatically triggers a response. Noise is not added in either model. However, our PDP model is intended to simulate all ensembles in the DO taxonomy, whereas Zorzi and Umilta's (1995) model is restricted to the Simon effect (Ensemble 3) only. Furthermore, our PDP model assumes the existence of an intermediate layer, whereas Zorzi and Umilta's (1995) model does not. In our PDP model, mutual inhibition and competition are assumed for every module, whereas in Zorzi and Umilta's (1995) model, they are assumed for the response module only.

Production System for SR Compatibility Tasks

Rosenbloom and Newell (1987) and John and Newell (1990) approached the issue of SR compatibility from the perspective of production system. For a given task, they first identify the rules required to achieve the goal and then these rules are implemented in terms of productions. Rosenbloom and Newell (1987) postulated only one type of production, but John and Newell (1990) distinguished three types of production rules, one each for perception, cognition, and motor action, respectively. They successfully simulated the SR congruity effect reported by Duncan (1977) and Fitts and Seeger (1953). However, it is not clear how the models developed by Rosenbloom and Newell (1987) and John and Newell (1990) would simulate the other findings in this field (e.g., the Stroop and Simon effects).

CONCLUSION

The PDP model of compatibility proposed in this article has incorporated principles of parallel and competitive processing (e.g., McClelland & Rumelhart, 1981) into the DO model of compatibility tasks (Kornblum, 1992; Kornblum et al., 1990) and has been employed to simulate RT performance in all eight ensemble tasks included in the DO taxonomy (Kornblum, 1992, 1994; Kornblum & Lee, 1995). The eight ensemble tasks are related to one another in terms of three types of overlap: relevant SR overlap, irrelevant SR overlap, and SS overlap. Our PDP model of compatibility consists of modules and nodes at three layers (input–intermediate–output). In the PDP model, the relevant or irrelevant SR overlap is implemented by the automatic lines and the SS overlap is implemented by the convergence of two input modules onto a common intermediate module. Based upon the common set of representational and processing assumptions that has received behavioral support, PDP networks are formulated for various ensembles. The PDP model provides a reasonable account for most of the major findings in the compatibility tasks included in the DO taxonomy. This model appears to have captured the strengths of both the DO model of compatibility tasks (especially the DO taxonomy) and the PDP modeling approach. Similar to the DO model but different from other computational models of compatibility tasks (e.g., Cohen et al., 1990; Zorzi & Umilta, 1995), our PDP model of compatibility offers a unified, principled account that is not limited to any specific compatibility task.

It should be noted that the present PDP model of compatibility is different from the DO model in terms of its detailed representational and processing assumptions, its principles of multiple, parallel pathways and continuous rather than discrete information processing, and its quantitative rather than qualitative simulations and fits. Of course, the PDP model of compatibility inherits the broad scope (e.g., the taxonomy of compatibility) from the DO model (Kornblum, 1992). However, the present PDP model of compatibility provides a different account for Ensemble 4 and a more elaborate account for Ensemble 8. Furthermore, it is able to accommodate psychological phenomena such as the Stroop effects in single- and mixed-carrier tasks.

REFERENCES

Barber, P. J., O'Leary, M. J., & Simon, J. R. (1994). Defining stimulus congruity: A rejoinder to Guiard, Hasbroucq, and Possamai (1994). *Psychological Research,* **56,** 213–215.

Cattell, J. M. (1886). The time it takes to see and name objects. *Mind,* **11,** 63–65.

Cohen, J. D., Dunbar, K., & McClelland, J. L. (1990). On the control of automatic processes: A parallel distributed processing account of the Stroop effect. *Psychological Review,* **97,** 332–361.

Cohen, J. D., & Huston, T. A. (1994). Progress in the use of interactive models for understanding attention and performance. In C. Umilta & Moscovitch (Eds.), *Attention and performance XV* (pp. 453–475). Cambridge, MA: MIT Press.

Cohen, J. D., Servan-Schreiber, D., & McClelland, J. L. (1992). A parallel distributed processing approach to automaticity. *American Journal of Psychology,* **105,** 239–269.

Cohen, J. D., Usher, M., & McClelland, J. L. (1998). A PDP approach to set size effects within the Stroop task: Reply to Kanne, Balota, Spieler, and Faust (1998). *Psychological Review,* **105,** 188–194.

Coles, M. G. N., Gehring, W. J., Gratton, G., & Donchin, E. (1992). Response activation and verification. In G. E. Stelmach & J. Requin (Eds.), *Tutorials in motor behavior* (Vol. 2, pp. 779–792). Amsterdam, North-Holland: Elsevier.

Coles, M. G. H., Gratton, G., Bashore, T. R., Eriksen, C. W., & Donchin, E. (1985). A psychophysiological investigation of the continuous flow model of human information processing. *Journal of Experimental Psychology: Human Perception and Performance,* **11,** 529–553.

Collins, A. M., & Loftus, E. F. (1975). A spreading-activation theory of semantic processing. *Psychological Review,* **82,** 407–428.

Cybenko, G. (1989). Approximation by superpositions of a sigmoidal function. *Mathematics of Control, Signals, and Systems,* **2,** 303–314.

Damasio, A. R., & Damasio, H. (1992). Brain and language. *Scientific American,* **267,** 88–95.

De Jong, R., Liang, C.-C., & Lauber, E. (1994). Conditional and unconditional automaticity: A dual-process model of effects of spatial stimulus–response correspondence. *Journal of Experimental Psychology: Human Perception and Performance,* **20,** 731–750.

Duncan, J. (1977). Response selection rules in spatial choice reaction tasks. In S. Dornic (Ed.), *Attention and performance VI* (pp. 49–61). Hillsdale, NJ: Erlbaum.

Eimer, M. (1995). Stimulus–response compatibility and automatic response activation: Evidence from psychophysiological studies. *Journal of Experimental Psychology: Human Perception and Performance,* **21,** 837–854.

Eriksen, B. A., & Eriksen, C. W. (1974). Effects of noise letters upon the identification of a target letter in a nonsearch task. *Perception and Psychophysics,* **16,** 143–149.

Eriksen, C. W., & Schultz, D. W. (1979). Information processing in visual search: A continuous flow conception and experimental results. *Perception and Psychophysics,* **25,** 249–263.

Fitts, P. M., & Deininger, R. L. (1954). SR compatibility: Correspondence among paired elements within stimulus and response codes. *Journal of Experimental Psychology,* **48,** 483–492.

Fitts, P. M., & Seeger, C. M. (1953). SR compatibility: Spatial characteristics of stimulus and response codes. *Journal of Experimental Psychology,* **46,** 199–210.

Georgopoulos, A. P., Lurito, J. T., Petrides, M., Schwartz, A. B., & Massey, J. T. (1989). Mental rotation of the neuronal population vector. *Science,* **243,** 234–236.

Glaser, M. O., & Glaser, W. R. (1982). Time course analysis of the Stroop phenomenon. *Journal of Experimental Psychology: Human Perception and Performance,* **8,** 875–894.

Glaser, W. R., & Glaser, M. O. (1989). Context effects in Stroop-like word and picture processing. *Journal of Experimental Psychology: General,* **118,** 13–42.

Gratton, G., Coles, M. G. H., Sirevaag, E. J., Eriksen, C. W., & Donchin, E. (1988). Pre- and post-stimulus activation of response channels: A psychophysiological analysis. *Journal of Experimental Psychology: Human Perception and Performance,* **14,** 331–344.

Green, E. J., & Barber, P. J. (1981). An auditory Stroop effect with judgments of speaker gender. *Perception and Psychophysics,* **30,** 459–466.

Guiard, Y., Hasbroucq, T., & Possamai, C. A. (1994). Stimulus congruity, irrelevant spatial SR correspondence, and display-control arrangement correspondence: A reply to O'Leary, Barber, and Simon (1994). *Psychological Research,* **56,** 210–212.

Hasbroucq, T., & Guiard, Y. (1991). Stimulus–response compatibility and the Simon effect: Toward a conceptual clarification. *Journal of Experimental Psychology: Human Perception and Performance,* **17,** 246–266.

Hedge, A., & Marsh, N. W. A. (1975). The effects of irrelevant spatial correspondence on two-choice response-time. *Acta Psychologica,* **39,** 427–439.

Hommel, B., & Prinz, W. (1997). *Theoretical issues in stimulus–response compatibility.* Amsterdam, North-Holland: Elsevier.

John, N. E., & Newell, A. (1990). Toward an engineering model of stimulus–response compatibility. In R. W. Proctor & T. G. Reeve (Eds.), *Stimulus–response compatibility: An integrated perspective* (pp. 427–479). Amsterdam, North-Holland: Elsevier.

Kanne, S. M., Balota, D. A., Spieler, D. H., & Faust, M. E. (1998). Explorations of Cohen, Dunbar, and McClelland's (1990) connectionist model of Stroop performance. *Psychological Review,* **105,** 174–187.

Kornblum, S. (1992). Dimensional overlap and dimensional relevance in stimulus–response and stimulus–stimulus compatibility. In G. E. Stelmach & J. Requin (Eds.), *Tutorials in motor behavior* (Vol. 2, pp. 743–777). Amsterdam, North Holland: Elsevier.

Kornblum, S. (1994). The way irrelevant dimensions are processed depends on what they overlap with: The case of Stroop and Simon-like stimuli. *Psychological Research,* **56,** 130–135.

Kornblum, S., Hasbroucq, T., & Osman, A. (1990). Dimensional overlap: Cognitive basis for stimulus–response compatibility—A model and taxonomy. *Psychological Review,* **97,** 253–270.

Kornblum, S., & Lee, J.-W. (1995). A study of stimulus–response compatibility with relevant and irrelevant stimulus dimensions that do and do not overlap with the response. *Journal of Experimental Psychology: Human Perception and Performance,* **21,** 855–875.

Kornblum, S., Stevens, G., Whipple, A., & Requin, J. (in press). The effects of irrelevant stimuli I: The time course of stimulus–stimulus and stimulus–response consistency effects with Stroop-like stimuli, Simon-like tasks, and their factorial combinations. *Journal of Experimental Psychology: Human Perception and Performance.*

Kornblum, S., & Zhang, H. (1991, June). *The time course of the automatic response activation process in stimulus–response compatibility*. Paper presented at ''Analytic Approaches to Human Cognition,'' Brussels, Belgium.

Lu, C.-H., & Proctor, R. W. (1994). Processing of an irrelevant location dimension as a function of the relevant stimulus dimension. *Journal of Experimental Psychology: Human Perception and Performance,* **20,** 286–298.

Lu, C.-H., & Proctor, R. W. (1995). The influence of irrelevant location information on performance: A review of the Simon and spatial Stroop effects. *Psychonomic Bulletin and Review,* **2,** 174–207.

MacLeod, C. M. (1991). Half a century of research on the Stroop effect: An integrative review. *Psychological Bulletin,* **109,** 163–203.

McClelland, J. L. (1992). Toward a theory of information processing in graded, random, and interactive networks. In D. E. Meyer & S. Kornblum (Eds.), *Attention and performance XIV* (pp. 655–688). Cambridge, MA: MIT Press.

McClelland, J. L., & Rumelhart, D. E. (1981). An interactive activation model of context effects in letter perception: Part I. An account of basic findings. *Psychological Review,* **88,** 375–407.

McClelland, J. L., & Rumelhart, D. E. (Eds.) (1986). *Parallel distributed processing* (Vol. II). Cambridge, MA: MIT Press.

Meyer, D. E., Irwin, D. E., Osman, A. M., & Kounios, J. (1988). The dynamics of cognition and action: Mental processes inferred from speed-accuracy decomposition. *Psychological Review,* **95,** 183–237.

Mozer, M. C. (1991). *The perception of multiple objects.* Cambridge, MA: MIT Press.

O'Leary, M. J., Barber, P. J., & Simon, J. R. (1994). Does stimulus correspondence account for the Simon effect? Comments on Hasbroucq and Guiard (1991). *Psychological Research,* **56,** 203–209.

O'Leary, M. J., Barber, P. J., & Simon, J. R. (1995). Does stimulus correspondence account for the Simon effect? Comments on Hasbroucq and Guiard (1991): Erratum. *Psychological Research,* **56,** 74.

Oliver, L. M., & Kornblum, S. (1991, November). *Dimensional overlap and population stereotype as joint predictors of SR compatibility.* Paper presented at the 32nd Annual Meeting of the Psychonomic Society, San Francisco, CA.

Phaf, R. H., Van der Heijden, A. H. C., & Hudson, P. T. W. (1990). SLAM: A connectionist model for attention in visual selection tasks. *Cognitive Psychology,* **22,** 273–341.

Posner, M. I., & Snyder, C. R. R. (1975). Attention and cognitive control. In R. L. Solso (Ed.), *Information processing and cognition: The Loyola symposium* (pp. 55–85). Hillsdale, NJ: Erlbaum.

Proctor, R. W., & Reeve, T. G. (1990). *Stimulus–response compatibility: An integrated perspective.* Amsterdam, North-Holland: Elsevier.

Reeve, T. G., & Proctor, R. W. (1990). The salient-feature coding principle for spatial- and symbolic-compatibility effects. In R. W. Proctor & T. G. Reeve (Eds.). *Stimulus–response compatibility: An integrated perspective* (pp. 163–180). Amsterdam, North-Holland: Elsevier.

Rosenbloom, P. S., & Newell, A. (1987). An integrated computational model of stimulus–response compatibility and practice. *The Psychology of Learning and Motivation,* **21,** 1–52.

Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning internal representations by error propagation. In D. E. Rumelhart & J. L. McClelland (Eds.), *Parallel distributed processing: Explorations in the microstructures of cognition* (Vol. 1, pp. 318–362). Cambridge, MA: MIT Press.

Rumelhart, D. E., & McClelland, J. L. (1982). An interactive activation model of context effects in letter perception: Part 2. The contextual enhancement effect and some tests and extensions of the model. *Psychological Review,* **89,** 60–94.

Schvaneveldt, R. W., & Staudenmeyer, H. (1970). Mental arithmetic and the uncertainty effect in choice reaction time. *Journal of Experimental Psychology,* **85,** 111–117.

Simon, J. R. (1969). Reactions toward the source of stimulation. *Journal of Experimental Psychology,* **81,** 174–176.

Simon, J. R. (1990). The effects of an irrelevant directional cue on human information processing. In R. W. Proctor & T. G. Reeve (Eds.). *Stimulus–response compatibility: An integrated perspective* (pp. 31–86). Amsterdam, North-Holland: Elsevier.

Simon, J. R., & Berbaum, K. (1990). Effect of conflicting cues: The ‘‘Stroop effect’’ vs. the ‘‘Simon effect.’’ *Acta Psychologica,* **73,** 159–170.

Simon, J. R., Sly, P. E., & Vilapakkam, S. (1981). Effect of compatibility of SR mapping on reactions toward the stimulus source. *Acta Psychologica,* **47,** 63–81.

Simon, J. R., & Sudalaimuthu, P. (1979). Effects of SR mapping and response modality on performance in a Stroop task. *Journal of Experimental Psychology: Human Perception and Performance,* **5,** 176–187.

Stoffels, E. J., & van der Molen, M. W. (1988). Effects of visual and auditory noise on visual choice reaction time in a continuous-flow paradigm. *Perception and Psychophysics,* **44,** 7–14.

Stroop, J. R. (1935/1992). Studies of interference in serial verbal reactions. *Journal of Experimental Psychology,* **18,** 643–662. [reprinted in *Journal of Experimental Psychology: General,* **121,** 15–23]

Umilta, A., & Nicoletti, R. (1992). An integrated model of the Simon effect. In J. Alegria, D. Holender, J. Junca de Morais, & M. Radeau (Eds.), *Analytic approach to human cognition* (pp. 331–350). Amsterdam: Elsevier.

Wang, H., & Proctor, R. W. (1996). Stimulus–response compatibility as a function of stimulus code and response modality. *Journal of Experimental Psychology: Human Perception and Performance,* **22,** 1201–1217.

Whitaker, L. A. (1979). Dual-task interference as a function of cognitive processing load. *Acta Psychologica,* **43,** 71–84.

Zhang, H. (1996). A further study on the Stroop effect: Early-selection, late selection, or both? *Proceedings of the Indiana Academy of Social Sciences*, **31,** 130–136.

Zhang, H., & Kornblum, S. (1998). The effects of stimulus–response mapping and irrelevant stimulus–response and stimulus–stimulus overlap in four-choice Stroop tasks with single-carrier stimuli. *Journal of Experimental Psychology: Human Perception and Performance,* **24,** 3–19.

Zhang, H., Rozzi, S., & Ross, J. (1998). *Interactions between stimulus–stimulus and stimulus–response compatibility: The case in which response-overlapping stimuli are relevant.* Unpublished manuscript.

Zhang, J., & Kornblum, S. (1997). Distributional analysis and De Jong, Liang, and Lauber's (1994) dual-process model of the Simon effect. *Journal of Experimental Psychology: Human Perception and Performance,* **23,** 1543–1551.

Zorzi, M., & Umilta, C. (1995). A computational model of the Simon effect. *Psychological Research,* **58,** 193–205.

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