Task switching without knowledge of the tasks.

C.L. Forrest (clf206@exeter.ac.uk)

H. Elchlepp (H.Elchlepp@exeter.ac.uk)

S. Monsell (S.Monsell@exeter.ac.uk)

I.P.L. McLaren (I.P.L.McLaren@exeter.ac.uk)

School of Psychology, College of Life and Environmental Sciences,

University of Exeter, UK.

Abstract

Task-cuing paradigms are typically taken to explore control of task-set. However, they can be construed as requiring not selection of a task-set, just retrieval of a cue+stimulus-->response (CSR) mapping. In this paper we considered performance in a task-cuing paradigm in which participants saw a color cue that indicated whether they should classify a digit as odd/even or high/low using one of two responses. Half the participants were instructed in terms of tasks (Task group) whilst the others were required to learn the CSR mappings without mention of tasks (CSR group). Predicted performance under CSR conditions was modeled using an APECS connectionist network. Both the model and CSR group produced small switch costs, mostly due to incongruent stimuli, and large congruency effects that reduced with practice. In contrast, the Task group produced a larger switch-cost and a smaller, stable congruency effect.

Keywords: task-switching, connectionist modeling, conditional discriminations, associative learning

CSR

Colour	Number	Key to press
RED	1	LEFT
YELLOW	1	LEFT
GREEN	1	LEFT
BLUE	1	LEFT
RED	4	LEFT
YELLOW	4	LEFT
GREEN	4	RIGHT
BLUE	4	RIGHT
RED	7	RIGHT
YELLOW	7	RIGHT
GREEN	7	LEFT
BLUE	7	LEFT
RED	8	RIGHT
YELLOW	8	RIGHT
GREEN	8	RIGHT
BLUE	8	RIGHT

Task

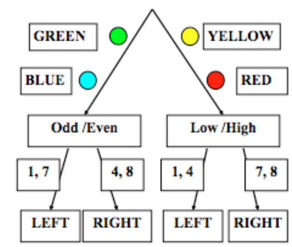

Figure 1 on the left shows the way in which the experiment was presented in the CSR condition and on the right in the Task condition.

Introduction

We often think of our behaviour as being governed by both higher-level cognitive control processes and lower-level associative processes (McLaren, Green & Mackintosh, 1994). Typically these processes are thought to operate simultaneously but with a degree of independence. This paper takes a task-cuing paradigm, typically taken as measuring the higher level cognitive control processes involved in changing between tasks (Monsell, 2003), and asks if the performance typically seen could instead be accounted for by lower level associative processes. This paradigm has been used widely to measure control processes in areas as diverse as aging (Mayr, 2001) and schizophrenia (Meiran, 2000) It is also commonly included in brain training packages as a way to improve your ability to multitask and pay attention. Given such widespread use, it is important to assess if the paradigm actually measures control processes at all; it has been argued that it does not (Logan and Bundesen, 2003; Schneider and Logan, 2005).

The response contingencies in many task-cuing experiments can be construed without any reference to tasks. This paper examines what happens when participants approach such an experiment without knowledge of the task-sets. Data and simulation suggest that they can learn the statistical structure of the experiment through the use of associative learning mechanisms, but their performance differs from that of participants construing the situation as one requiring task-selection and switching.

To clarify this, let us consider the task-cuing paradigm that we used. Under standard instructions in this paradigm participants are told, for example, that if the background circle is blue or green then they should classify the digit they then see as odd/even, where odd requires a response with the left key and even with the right. However, if the background circle is red or yellow they should classify the digit as higher/lower than 5, with a right response for high, and a left response for low. This is the "task-set" construal of what is required, as illustrated on the right of Figure 1. Yet participants do not need knowledge of these tasks to know how to respond, as the color and the number combination is completely predictive of the required response, e.g. a 4 on yellow will always require a left response. Hence, especially with small stimulus set, it is entirely possible for participants in a task cuing experiment not to use the task-sets at all, in which case the experiment is not measuring task-based control processes.

In the experiment reported here we compare a group who are explicitly instructed to use the task-sets with one that has no knowledge of the underlying task-set structure. In order to examine whether, and in what ways, performance differs between the two conditions we will consider three of the common effects found within the task-switching literature: the switch cost, the reduction in the switch cost with time to prepare (RISC effect) and the congruency effect (Monsell, 2003, Kiesel et al, 2011).

It is typically found that when participants change from performing one task to performing another task there is a switch cost; participants are generally slower and less accurate on a task-switch trial than a task-repeat trial. Participants are also able to reduce this switch cost when they are given more time to prepare the task set, i.e. when there is a longer time between the cue (colored circle), which indicates the task-set, appearing and the stimulus (number) appearing the switch cost declines. Explanations of these effects have appealed to task set inertia (Allport, Styles & Hsieh 1994) —conflict due to residual activation of the previous task set - and/or the need to perform a task set reconfiguration process (Rogers & Monsell, 1995) which reduces conflict if performed before the stimulus appears. But, according to the compound-cuing model of Logan and colleagues (Logan & Bundesen, 2003; Schneider & Logan, 2005) participants simply retrieve the response associated with the combination of cue and stimulus, so these effects cannot be taken as hallmarks of control.

In the task-cuing experiment already described, the responses for the two tasks are mapped onto the same keys, i.e. the left key represents odd and high, whilst the right key represents even and low. Hence for some numbers the response is always the same regardless of the task cued, e.g. 1 always requires a left response; these are called *congruent* stimuli. For other numbers the response changes with the task cued, e.g. 4 requires a left response if the task is high/low but a right response if the task is odd/even; these are *incongruent* stimuli. Typically, it is found that participants are faster and more accurate for congruent than incongruent stimuli. As with the switch cost and reduction in switch cost (RISC) effect there have been both task-set based and non-task-set based explanations of this congruency effect. Some researchers have argued that the congruency effect is due to response conflict from the currently irrelevant task-set (Kiesel et al, 2011). Other researchers have argued that it is caused by associative interference, as the incongruent stimuli are linked to both responses whilst the congruent stimuli are only linked to one (Kiesel, Wendt & Peters, 2007).

In this experiment we asked whether the switch cost, the RISC effect and the congruency effect depend on how the participants construe the experiment, i.e. whether in terms of tasks or cue + stimulus to response (CSR) mappings.

In addition to considering these standard task switching effects we also considered the effect of introducing novel stimuli (cf. Rogers & Monsell, 1995). This is particularly relevant for assaying the difference between switching among stimulus-classification task rules versus applying a single set of learned CSR rules. For participants using tasks there should be little impact of introducing new stimuli. There might be a slight novelty effect, but they should be able to treat the new stimuli in the same way as the old, continuing to apply the same classification rules. However, participants with no knowledge of the task-sets have no way of knowing how to respond to the novel numbers; they should be reduced to learning how to respond by trial and error, and one would expect performance on the new numbers to be dramatically worse than performance on the old numbers.

Modeling

As summarized above there is plenty of evidence to suggest how participants typically perform in a task-cuing paradigm with knowledge of the tasks (Monsell, 2003, Kiesel et al, 2010). In order to attempt to predict how participants would perform in the task-cuing experiment described above without knowledge of the task-sets we simulated performance using an associative model. The mappings for the congruent stimuli are shown in outline in Table 1. It is immediately evident that they should be easily captured by an associative model, as the stimuli in isolation predict the correct response.

		Cues (Color)			
		W (blue)	X (green)	Y (red)	Z (yellow)
	A (1)	**L**	**L**	**L**	**L**
Stimuli	B (3)	L	L	L	L
(Digit)	C (6)	R	R	R	R
	D (8)	**R**	**R**	**R**	**R**

Table 1 The associative structure of the congruent trials. L indicates a left R a right response. Boldface rows indicate example initially trained stimuli; the others introduced later

The incongruent stimuli, shown in Table 2, are more of a challenge for an associative model. There is evidence from rabbits (Saavedra, 1975) and humans (Livesey et al, 2011) that, although these stimuli are harder to learn than the congruent stimuli, they can be learned. However, a single layer error-correcting model, e.g. Rescorla-Wagner (1972) would be unable to learn this structure.

		Cues (Color)			
		W (blue)	X (green)	Y (red)	Z (yellow)
	E (2)	R	R	L	L
Stimuli	**F (4)**	**R**	**R**	**L**	**L**
(Digit)	**G (7)**	**L**	**L**	**R**	**R**
	H (9)	L	L	R	R

Table 2 shows the associative structure of the incongruent trials using the conventions employed in Table 1.

In addition to the difference in performance on incongruent and congruent trials, one might also expect effects of cue equivalence (Honey & Ward-Robinson, 2002; Hodder, George, Kilcross & Honey, 2003). These studies trained rats or humans (respectively) with the same contingencies as the incongruent trials. They found that cues that indicated the same outcome from stimuli became equivalent e.g. here W and X would become equivalent as would Y and Z, in that there would be a greater degree of generalization between W and X than W and Y. Honey and Ward-Robinson (2002) found that a modified connectionist model was able to account for their data by allowing the same hidden unit to carry the mappings for equivalent cues. We used a model from the same class as their chosen model. The model is known as APECS (McLaren, 1994, 2011; LePelley & McLaren, 2001) and has a good record in modeling human learning and memory. APECS has the basic characteristics of a back-propagation network (Rumelhart, Hinton and Williams, 1986), i.e. it is a standard feedforward error correcting system with input, hidden and output layers that has been modified in two key ways:

Learning algorithm and rates The APECS learning algorithm allows the learning rates to change in an adaptive manner. On each trial, the hidden unit with the largest error receives a higher learning rate than the other hidden units. This effectively means that one (or a few) hidden unit(s) is (are) selected to carry each mapping from input to output.

Bias The APECS group of models also includes an adaptive bias whose learning rate is varied to prevent catastrophic interference to old learning occurring when new information is learnt (McCloskey and Cohen, 1989). The adaptive bias lowers the chances of the same hidden unit being used by a different mapping and hence prevents the previous learning being over-written.

Modeling Method

Sequencing As in the experiment below, one third of trials were "switch" trials (defined with respect to the task-set representation). The cue changed color on every trial, and either of two colors signaled each task. The number of times a given stimulus appeared in a given task on a repeat or switch trial was constrained. There were 14 blocks of 49 trials in total. For the first 10 blocks only 4 stimuli were possible, whilst for the last 4 blocks 8 stimuli were possible.

Representation and Architecture The 4 cues and 8 digit stimuli were represented discretely with one input unit coding for each. The responses were also represented discretely, and the model was trained to 0.9 for the correct response and 0.5 for the wrong one. It was trained to auto-associate the input with the output, with certain output units active only if a specific input unit was active. The network had three layers: 16 input units, 14 hidden units and 18 output units.

Learning parameters The fast learning rate was set to 0.8 whilst the slow learning rate for the unselected units was 0.0005. For the bias the learning rate for selected hidden units was 0.5 and for others was 0.005.

Output The output of the model was assessed by subtracting the difference between the actual activations of the two response output units (desired response – undesired response) from the target difference (0.4). On this measure larger scores mean worse performance.

Modeling Results

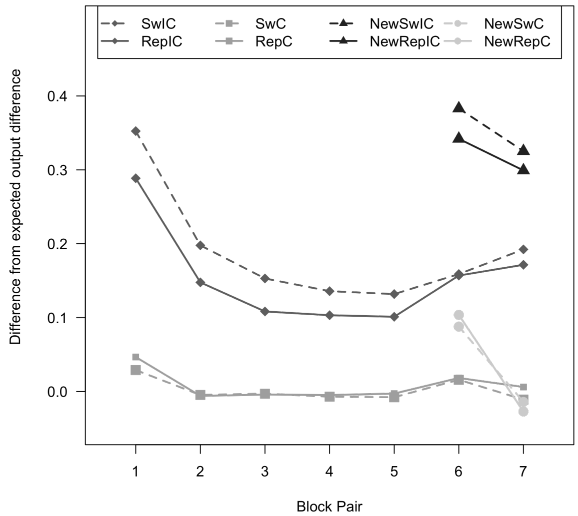

Figure 2 shows the performance of the model plotted as the difference between the desired output difference (0.9-0.5) and the actual output difference – hence 0.4 represents no learning whilst 0 represents perfect learning. The points are plotted by block pair, congruency, switch and new stimuli. Darker lines represent incongruent stimuli (IC) with diamonds representing the originally trained stimuli and triangles the transfer stimuli (New). Lighter lines represent congruent stimuli, with squares representing the originally trained stimuli and circles the transfer stimuli (New). Dotted lines represent switch trials (Sw) and solid lines repeat trials (Rep).

The results were analyzed across block pairs 2-5 (as block pair 1 was a practice block) using an ANOVA with the factors, block pair, congruency, and switch.

Task switches There was a small but significant effect of "task switch"; the model's performance was worse on switch than repeat trials (switch: 0.075, repeat: 0.055), $F(1,31)=49.5$, $p<0.001$ — see Figure 2.

Congruency There was a large and significant effect of congruency; the model's performance was worse on incongruent than congruent trials (congruent: 0.095, incongruent: 0.035), $F(1,31)=168.5$, $p<0.001$.

Switch by congruency. The switch cost was significantly larger for incongruent trials (0.04) than the congruent trials (-0.002), $F(1,30)= 10.4$, $p<0.01$.

Acquisition effects. Overall performance reliably improved from block pair 2 to 5 (Figure 2), $F(3, 93)= 44.3$, $p<0.001$. The two-way interaction between block pair and congruency was significant $F(3, 93)= 43.3$,$p<0.001$ This interaction can be seen in Figure 2 which shows the congruent stimuli being learnt quickly whilst the incongruent stimuli take longer to learn.

Transfer to new stimuli The effect of transfer was analyzed by comparing the performance on the newly introduced stimuli with that on the old stimuli in block pairs 6 and 7. As expected, the model found the novel stimuli

(0.189) much harder than the previous stimuli (0.089), $F(1,31)=509$, $p<0.001$.

Modeling Discussion

The model predicts a large congruency effect which varies over blocks, a small switch cost which is only present in the incongruent trials and a significant disadvantage for newly introduced stimuli. This gives a clear indication what we might expect from participants if they were performing on an associative basis. It is also different from the typical task-cuing results where the switch cost is usually larger than the congruency effect. We now consider the empirical data obtained from participants trained on this task under Task or CSR instructions.

Behavioral Method

Participants The participants were 35 psychology undergraduates (mean age = 20.3 years, 7 males) at the University of Exeter. Participants took part for course credit and a bonus payment, which was contingent on their performance (average payment £2.04, range £1.50-£2.50).

Stimuli The task cues were circles (6.7º of visual angle), filled with: blue (RGB: 0, 0, 255), red (RGB: 255, 0, 0), green (RGB: 0, 255, 0) or yellow (RGB: 255, 255, 0); in the center of the cue, the digit stimulus was then displayed in 60-pt Courier bold font (1.3º of visual angle). The two sets of digits used were 1,4,7,8 and 2,3,6,9 – these sets were used as on average the values are the same distance from 5 (the criterion value for 'high'/'low'. An iMac was used to display the stimuli using Matlab 2008a with Psychtoolbox.

Design and procedure The sequencing was constrained in the same way as for the model, with the addition of a variable CSI that was alternated by blocks to give a long CSI of 1200 ms and a short CSI of 100 ms. For the first block pair, participants were given a piece of paper with correct responses in the format of the relevant Task or CSR diagram (as in Figure 1); in addition participants in the Task condition were given standard task-set instructions verbally and on-screen, whereas participants in the CSR condition were directed to learn cue+stimulus → response mappings on the basis of trial by trial feedback.

After 5 block pairs the second set of four stimuli was introduced in addition to the set already in use. No mention of the new numbers was made prior to their appearance. Participants were debriefed using a structured questionnaire, and replaced if their reported strategy differed from that instructed, i.e. if they induced the tasks in the CSR group, or failed to use the tasks as instructed in the Tasks group. Two participants in the Task group (who did not mention using tasks) and one participant in the CSR group (who induced one of the tasks) were replaced in this way.

Behavioral Results

The results were analyzed using an ANOVA as for the model, with the additional between-subjects variable of instructions and within subjects variable of CSI.

Task switches and instruction. There was a much larger switch cost in the Task group (160 ms) than in the CSR group (18.6ms), $F(1,30)=16.0$, $p<0.001$ — see Figure 3. The switch costs were reliable for the Task group, $F(1,15) = 22.4$, $p<0.001$, and nearly reliable for the CSR group, $F(1,15) = 3.24$, $p=0.092$. For errors, there was a near reliable interaction between instruction group and task switch/repeat, $F(1,30)=3.13$, $p=0.087$: the switch cost for the Task group was a reliable 2.9%, $F(1,15)= 11.9$, $p<0.01$, and for the CSR group 1.2%,also reliable, $F(1,15)=5.46$, $p<0.05$.

Preparation and instruction. As Figure 3 shows, preparation reduced the RT switch cost in the Task group from 213 ms (4.5%) in the short-CSI blocks to 107 ms (1.4%) in the long CSI blocks, this was significant in the RTs, $F(1,15)=6.23$, $p<0.05$ and nearly so in the errors, $F(1,15)=3.96$, $p=0.065$. There was no such effect in the CSR group, for whom the switch cost was 16 ms (0.9%) in the short-CSI blocks and 21 ms (1.5%) in the long-CSI blocks $F<1$. The interaction was reliable in the RTs, $F(1,30)= 5.67$, $p<0.05$ and nearly significant in the errors, $F(1,30)=3.91$, $p=0.057$. Participants in the Task condition also showed a general preparation effect, whereby if only the task-repeat trials are considered they were faster with a long-CSI (611ms) than with a short-CSI (853ms), $F(1,15) = 63.8$, $p<0.001$. For the same contrast the CSR group was slightly, but not reliably, slower in the long-CSI (776ms) than at the short-CSI (745ms) condition, , $F(1,15) = 2.55$.

Congruency and instruction. RT and error rate showed (Figure 3) a much larger effect of congruency in the CSR group (346 ms, 7.4%) than in the Task group (91 ms, 6.1%); the interaction was highly reliable for RTs, $F(1,30)=23.9$, $p<0.001$, but not for error rate, $F<1$. In separate analyses, the congruence effect was reliable for both the Task group, $F(1, 15) =6.26$, $p<0.05$, for RTs, and $F(1,15)=33.8$, $p<0.001$, for errors, and the CSR group, $F(1,15) = 84.5$, $p<0.001$, for RT, and $F(1,15)=11.3$, $p<0.01$, for errors.

Switch by congruency. In agreement with the model the switch cost was larger for incongruent trials for the CSR group (30ms, 2%) than congruent trials (7ms, 0.4%). Similarly for the Task group the switch cost was larger for incongruent trials (161ms, 4.8%) than congruent trials (69ms, 1.1%). There was an overall significant interaction between task switch and congruency in the errors, $F(1,30)= 10.4$, $p<0.01$, but not in the RTs. This effect did not differ between the two experimental conditions in the error data or RTs.

Acquisition. Overall performance improved from block pair 2 to 5 (Figure 4), and this was reliable in RTs and errors, $F(2.7,79.6)=43.3$, $p<0.001$, $F(2.7, 79.6)=4.60$, $p<0.05$. The three-way interaction between block pair, congruency and instructions was significant in the RTs only, $F(2.7, 79.6)= 7.35$,$p<0.01$ and marginally so in the errors, $F(2.7, 79.6)$, 2.23, $p=0.095$. Separate analyses revealed a highly significant block pair by congruency interaction in the CSR condition, RT: $F(2.3,34.6)= 9.40$, $p<0.001$, errors: $F(2.3,34.6)=6.94$, $p<0.05$, but not in the Task group, $F<1$. This interaction can be seen in Figure 4 which shows the congruent trials being learnt quickly by the CSR group whilst the incongruent trials took longer to learn, a pattern similar to the predictions made by the model.

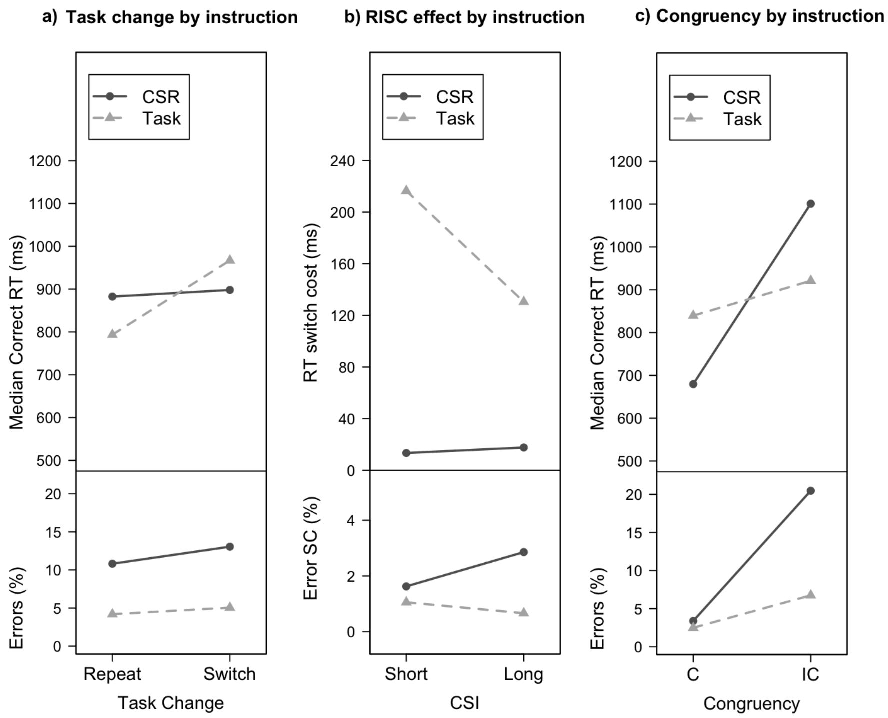

Figure 3 shows switch cost reductions in switch cost and the congruency effect, for the Task and CSR groups.

Introduction of new stimuli. Figure 4 also illustrates that the two groups were differentially affected by the introduction of novel stimuli at block pair 6. The new stimuli seem to be accommodated with ease by the Task group, but for the CSR group they clearly cause problems, especially incongruent stimuli. As for the model, the effect of new stimuli was analyzed by comparing the performance on the novel stimuli with that on the old. As expected, the CSR group was more affected by the introduction of new stimuli; their RT (error rate) was much larger for the new stimuli 1201 ms (21.7%) than the old stimuli 946 ms (4.1%), whereas in the Task group performance on the new stimuli, at 780ms (7.5%) was more equivalent to that of the old stimuli, 731 ms (4.8%). This difference was supported by a significant interaction in both the RTs, $F(1,25)=23.8$, $p<0.001$ and errors, $F(1,30)=37.7$.

Discussion

There was a clear difference in the performance of the two groups. The Task group exhibited a large switch cost, which was substantially reduced by the opportunity to prepare. In contrast, the CSR group had a smaller switch cost, which derived largely from the incongruent stimuli and was unaffected by CSI. The CSR group had a much larger congruency effect, which was modulated with practice because congruent stimuli were learnt much faster than incongruent stimuli. In contrast the Task group exhibited a smaller congruency effect which was much more stable over practice.

These differences in the performance of participants with and without knowledge of the task-sets suggest that there is merit in theories of performance in task-cuing paradigms that appeal to task-set. However, given that participants who had no knowledge of the tasks showed significant "switch costs" and congruency effects also indicates that these phenomena are not *per se* indices of top-down control of task-set (as Logan & Bundesen, 2003, have also argued, for different reasons). Hence, part of the switch cost seen in the Tasks group might have the same source as for the CSR group, and the congruency effect in the Task group might be an ameliorated version of that seen in the CSR group, with top down task-set control helping to shield against associative interference (Dreisbach & Haider, 2009). However, the marked differences in performance between the groups — the much larger switch cost and its reduction with preparation in the Tasks group, and the much larger congruence effects in the CSR group — clearly suggested a qualitative difference in processing strategy between them. The effects of practice and transfer, with the CSR group's rapid learning of the congruent stimuli and difficulty with the transfer test contrasting with the relatively stable switch costs over practice, and good transfer for the Tasks group, also pointed to a substantial difference in processing strategy between groups, and highlights one of the advantages of a task-set strategy – the ability to generalize to novel cases.

Moreover, the data of the CSR group seem in agreement with the behavior of an associative learning network. All of the effects predicted by the model were present in the CSR

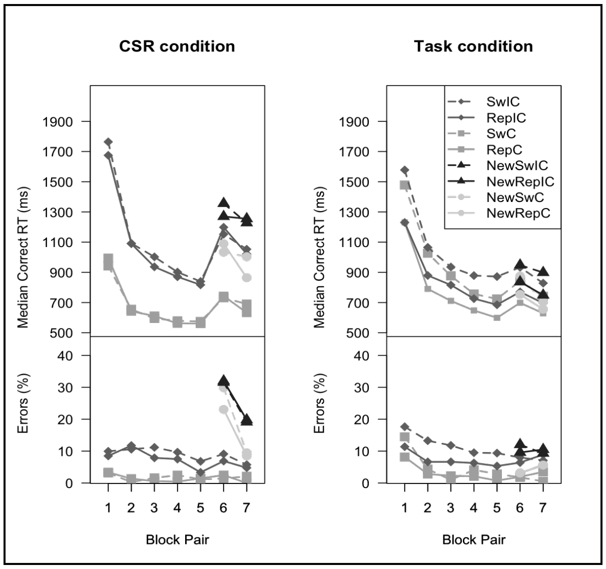

Figure 4 shows the performance over block pairs in the same way as Figure 2.

group: a large congruency effect and its modulation by practice, a modest "switch cost" due mostly to the incongruent stimuli, and a marked disadvantage in coping with new stimuli. This is certainly consistent with the suggestion that this group's performance was dependent on associative learning. We conclude that there is evidence to suggest that when participants perform in a task-cuing paradigm without knowledge of the tasks, they produce a distinctive pattern of results which is in line with the predictions of an associative model. If one is interested in using task-cuing to measure control processes, it may be wise to check for use of a CSR strategy, and to use conditions (e.g. larger stimulus sets) that discourage it.

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