Episodic and semantic components of the compound-stimulus strategy in the explicit task-cuing procedure

CATHERINE M. ARRINGTON and GORDON D. LOGAN
Vanderbilt University, Nashville, Tennessee

The explicit task-cuing procedure is commonly used to study executive control processes involved in set switching, but performance in this task-switching procedure may be accomplished without switching tasks. Subjects may perform both tasks by using a compound-stimulus strategy, in which subjects encode the cue, encode the target, and use the combination as a compound retrieval cue to choose the appropriate response. We manipulated the number of targets (8, 16, 32, or 640) that subjects experienced in a four-cue/two-task procedure to separate episodic and semantic memory retrieval components of the compound-stimulus strategy. Cue repetitions were faster than task repetitions, and task repetitions were only slightly faster than task alternations, suggesting that cue repetition effects account for the bulk of the difference between repetitions and alternations. We found the same effects with all target set sizes. The results are consistent with use of a semantic compound-stimulus strategy.

The coordination of perceptual, cognitive, and motor processes to serve a given goal and the ability to reconfigure these processes in response to changes in goals are considered to be executive control processes (Logan, 1985; Meyer & Kieras, 1997; Norman & Shallice, 1986). The study of executive control in the cognitive psychology laboratory generally involves situations in which goals governing task performance must be instantiated, maintained, or switched in the context of competing demands. The *explicit task-cuing* procedure is frequently used to study processes of executive control (Meiran, 1996; Sudevan & Taylor, 1987). The purpose of this article is to examine the role of episodic and semantic memory retrieval strategies in this procedure.

In the explicit task-cuing procedure, two or more tasks are interleaved within a block of trials in a random order, and an explicit cue indicates which task to perform on the current trial. Since tasks are interleaved, individual trials can be either task repetitions or task alternations. Response time (RT) is typically shorter for repetitions than for alternations. The difference in RT provides a measure of *switch costs*. Switch costs are commonly thought to reflect the time necessary to carry out an en-

dogenous act of set switching (Arrington, Altmann, & Carr, 2003; Arrington & Logan, 2004; Logan & Gordon, 2001; Meiran, 1996; Rogers & Monsell, 1995; Rubinstein, Meyer, & Evans, 2001). This interpretation of the difference in RTs is based on assumptions about what cognitive processes are engaged in performing each type of task transition. On both types of trials, the subject must first encode the cue. If the cue is the same as that in the previous trial, the subject simply waits for the target onset and processes the target with the task set that was instantiated on the last trial. If the cue is different from that in the previous trial, the subject engages in an endogenous act of set switching before processing and responding to the target. The addition of this act of set switching increases RT.

Recently, researchers have challenged the standard interpretation of switch costs in explicit task-cuing studies—namely, that they reflect the duration of an endogenous act of control whereby the executive switches task sets (Altmann, 2002; Logan & Bundesen, 2003). An alternative interpretation is that switch costs can be attributed to cue-encoding benefits on repetition trials, rather than endogenous set-switching processes. In this interpretation, differences between repetitions and alternations result from a faster cue-encoding process when the same cue was encoded on the previous trial.

Four-Cue/Two-Task Explicit Task-Cuing Procedure

One way that researchers have tested this alternative account is with a modified version of the explicit task-cuing procedure that involves two separate cues for each task (Logan & Bundesen, 2003, in press; Mayr & Kliegl, 2003). In this four-cue/two-task procedure, each task is

cued by two different cues. For example, the two tasks might involve judgments about digits: a magnitude judgment cued with either "magnitude" or "high–low" and a parity judgment cued with either "parity" or "odd–even." This procedure generates three different task transitions: *cue repetitions*, where the cue and the task remain the same as those on the previous trial; *task repetitions*, where the cue changes but the task remains the same as that on the previous trial; and *task alternations*, where both the cue and the task are different from those on the previous trial.

The cue repetition and task alternation conditions represent the typical conditions in an explicit cuing procedure, and both the standard endogenous act of control account and the alternative cue repetition benefit account would predict large differences between these conditions. The task repetition condition is the diagnostic condition separating these two accounts. The standard account predicts that task repetitions will produce RTs similar to those for cue repetitions, since the task does not change from one trial to the next and, thus, no set switching is involved. The alternative account predicts that task repetitions will produce RTs similar to those for task alternations, because the cue changes from one trial to the next and, thus, cue encoding cannot benefit from repetition.

Logan and Bundesen (2003) tested these predictions, using the four-cue/two-task method. In two experiments, one using the magnitude and parity judgments described above and one using left/right and above/below judgments of spatial locations, they found that cue repetitions were much faster than task repetitions but that task repetitions were only slightly faster than task alternations. The difference was significant in only one of the two experiments. On the basis of these and other findings, they concluded that the explicit task-cuing procedure does not necessarily involve an endogenous act of set switching (see also Logan & Bundesen, in press).

In a similar series of experiments using color and shape judgments in the four-cue/two-task procedure, Mayr and Kliegl (2003) also found a large benefit for cue repetitions over task repetitions but, in addition, found an equally large benefit for task repetitions over task alternations. On the basis of their results, they concluded that standard switch costs result from both cue switch and task switch costs, which occur during two processing stages involved in task switching. The first stage involves cue-based retrieval of the current task rules from long-term memory. The second stage involves application of those rules to the target stimulus.[1]

Logan and Bundesen (2003) proposed a compound-stimulus strategy to account for subjects' performance in the explicit task-cuing procedure, based on the idea that the procedure provides enough information on each trial to uniquely specify the correct response (e.g., the cue "magnitude" and the target "7" specify the "4" key). They proposed that subjects respond to combinations of cues and targets. Each task can then be performed with the same task set (i.e., encode the cue, encode the target,

and retrieve the appropriate response), thus removing any need for set switching. This compound-stimulus strategy accounts for their results: Cue repetitions should be faster than task repetitions and task alternations, because the cue-encoding process is faster when the cue repeats. Task repetitions should be no faster than task alternations, because the cue changes in both cases. The present article addresses different versions of Logan and Bundesen's (2003) compound-stimulus strategy. It does not try to distinguish the compound-stimulus strategy from Mayr and Kliegl's (2003) account.

Episodic Versus Semantic Compound-Stimulus Strategies

The compound-stimulus strategy may be implemented in two ways. First, cue–target pairs may be associated with particular responses in a relatively uninterpreted manner (e.g., "squiggle1" and "squiggle2" mean "press key X"). Such a strategy would rely on episodic retrieval of past instances when specific cue–target pairs were associated with particular responses. This strategy may require several repetitions of cues and targets before reliable associations develop (Logan, 1988). In Logan and Bundesen's (2003) experiments, as in most task-switching experiments, there was a small number of target stimuli (eight digits or four spatial locations), resulting in a small number of cue–target stimulus pairs (32 or 16) that repeated throughout the experiment, making this episodic compound-stimulus strategy possible. Second, cue–target pairs may be interpreted by the subject and then used as compound cues to retrieve information from semantic memory. Subjects presumably have information about digit magnitude and parity already in semantic memory and, thus, both tasks can be accomplished with the same task set: identify the cue, identify the target, use them as a joint retrieval cue, and report what they pull out of memory (e.g., "odd–even" and "7" retrieve "odd," so the response corresponding to *odd* is executed). This semantic version of the compound-stimulus strategy does not require any experience with the stimuli during the experiment. Subjects can rely on preexperimental associations that are already present in semantic memory before the first trial.

In the present experiment, we contrasted the episodic and the semantic versions of the compound-stimulus strategy. We distinguished the strategies empirically by varying the number of targets the subjects experienced (8, 16, 32, or 640 targets) and, thus, the number of times a target was presented within the experiment (80, 40, 20, or 1 presentations). In order to manipulate the number of targets, we developed two tasks in which verbal stimuli and semantic category judgments were used: origin and size. The tasks were cued by name cues "origin" or "size" or by mapping cues, such as "living nonliving" or "large small".

The episodic compound-stimulus strategy requires repeated experience with the same set of cues and targets, so the subjects should not be able to use it in the 640-target

condition, where each target is presented only once. The subjects should be more likely to use episodic retrieval as the number of targets decreases and the number of target repetitions increases. Thus, if the subjects are only able to use an episodic compound-stimulus strategy, in the present experiment there should be an interaction between task transition condition and the number of targets. The difference between task repetitions and task alternations should be smaller the smaller the number of targets. Thus, with 640 targets, the task transition effect should resemble Mayr and Kliegl's (2003) results, suggesting that there is task switching when the task changes. However, with eight targets, the data should resemble Logan and Bundesen's (2003) results, suggesting that subjects retrieve responses from memory without task switching. The intermediate conditions should show intermediate results.

The semantic compound-stimulus strategy requires no prior experience with the targets. If subjects use this strategy, the number of targets should have no effect on the task transition conditions. Cue repetitions should be faster than task repetitions, and task repetitions should be no faster than task alternations, regardless of the number of targets.

Finally, it is possible that subjects use both episodic and semantic strategies. The semantic compound-stimulus strategy may be used early in the session when cues and targets are interpreted and used jointly to probe semantic memory. The episodic compound-stimulus strategy may be used later in the session after associations between individual cue–target pairs and responses have been established. If both episodic and semantic strategies are implemented, the number of targets should not interact with task transition conditions, but RT should be smaller overall when the episodic compound-stimulus strategy is used (8-, 16-, and 32-target conditions) than when the semantic compound-stimulus strategy is used (640-item condition), showing a speed-up in responding as memory retrieval becomes episodic (Logan, 1988).

Modeling the Time Course Function

Logan and Bundesen (2003) developed formal models that capture alternative interpretations of the time course function, the decrease in both RTs and switch costs over increasing stimulus onset asynchrony (SOA). They proposed three formal models: Model 1 assumes that switch costs arise from an endogenous act of control necessary on alternation trials (representing the modal interpretation of switch costs), Model 2 assumes that switch costs arise from a benefit for encoding the cue on repetition trials, and Model 2+1 assumes a combination of these two components. In their study, Model 1 fit the data most poorly. Model 2 provided a substantially better fit to the data. Model 2+1 fit the data slightly better than did Model 2, but this improvement in fit was bought at the cost of unrealistically small estimates of the set-switching time and violations of the fundamental assumptions of the model (see also Logan & Bundesen, in press). These findings support a compound-stimulus strategy account

of switch costs in the explicit-cuing procedure, rather than an endogenous act of set switching.

Building on this work, we formalized three models and fit them to the time course functions in our experiment. Since Model 1 was unable to account for the data from the four-cue/two-task procedure, we did not fit that model. Model 2 instantiates the compound-stimulus strategy by assuming only a benefit for cue encoding on repetition trials. Both Models 2+1 and Model 3 assume a cue-encoding benefit on cue repetition trials and an additional component on task alternation trials but differ in terms of when that additional component takes place. Model 2+1 assumes an endogenous act of set switching in preparation for the upcoming task that occurs during the SOA between cue and target presentation. Model 3 assumes a benefit in target processing for repetition trials that can be modeled by allowing the time to respond to the target stimulus to vary between repetitions and alternations. Model 3 represents one possible formalization of the two-process account of Mayr and Kliegl (2003). It may also be thought of as capturing residual switch costs, because a difference in target-processing times for task repetitions and task alternations represents a process that cannot be initiated until the target stimulus appears.

In each of the models, the time course function is modeled in terms of the cumulative distributions of finishing times for the cue-encoding process and the set-switching process (if set switching occurs). The reduction in mean RT as a function of SOA results from the mixture of trials in which these component operations have been carried out prior to target onset and trials in which these operations must be completed following target onset, thus impacting the RT. At an SOA of zero, when the cue and the target are presented at the same time, the RT to the target includes the time to encode the cue and the time to switch task set (if set switching occurs), along with the time to process and respond to the target stimulus itself. As SOA increases, the probability that the cue is encoded and the task set is switched prior to the onset of the target increases. When SOA is long enough, cue encoding and set switching are complete before the onset of the target, and RT reflects only the time necessary to process and respond to the target. As SOA increases, the probability that RT will reflect only the time necessary to process the target increases, and thus, mean RT decreases.

The probability that cue encoding and set switching have occurred is a function of the distribution of finishing times for those processes. In the present models, we assume that these distributions are exponential. The exponential distribution is frequently used to model cognitive processes in stochastic models of RT (e.g., Townsend & Ashby, 1983). The exponential distribution provides a simple mathematical equation with a single parameter. This parameter represents the processing rate, which is also the reciprocal of the mean of the distribution (for further justification of this assumption, see Logan & Bundesen, 2003).

Model 2. Model 2 assumes that the switch costs seen in the explicit task-cuing procedure result from a benefit for cue encoding on repetition trials. This assumption is implemented by allowing the mean cue-encoding times for repetitions and alternations to be separate parameters, with the constraint that mean cue-encoding time is shorter for repetitions than for alternations. Thus, mean RT on cue repetition trials can be modeled as

$$RT = RT_{Base} + \mu_r \cdot \exp(-SOA/\mu_r), \qquad (1)$$

and mean RT on task repetition and task alternation trials as

$$RT = RT_{Base} + \mu_a \cdot \exp(-SOA/\mu_a). \qquad (2)$$

In both equations, RT_{Base} reflects the time to process the target, μ_r and μ_a represent the mean cue-encoding time when the cue is repeated and when the cue is not repeated, respectively, and $\mu_r < \mu_a$. Note that Model 2 assumes no residual switch cost.

Model 2+1. Model 2+1 assumes both an endogenous act of set switching and a benefit for cue encoding. On cue repetition trials, mean RT is calculated using Equation 1. On task repetition trials, mean RT is calculated using Equation 2. On task alternation trials mean RT is

$$RT = RT_{Base} + \exp(-SOA/\mu_a) \cdot (\mu_a + \mu_s)$$
$$+ \frac{1/\mu_a}{1/\mu_a - 1/\mu_s} \cdot \left[\exp(-SOA/\mu_s) \right.$$
$$\left. - \exp(-SOA/\mu_a) \right]. \qquad (3)$$

where RT_{Base} is the time necessary to process and respond to the target, which is the same in all conditions, μ_a is the mean cue-encoding time when the cue alternates, and μ_s is the mean set-switching time. Model 2 is nested within Model 2+1, because if μ_s is set to 0, Equation 3 reduces to Equation 2. Note that Model 2+1 also assumes no residual switch cost.

Model 3. Model 3 assumes a benefit for cue encoding when the cue repeats, as well as a benefit for target processing when the task repeats. The benefit for cue encoding is implemented by allowing mean cue-encoding time for cue repetitions to be separate from mean cue-encoding time for task repetitions and task alternations, with the constraint that mean cue-encoding time is shorter for cue repetitions. The benefit for target processing is implemented by allowing RT_{Base} to be the same for cue repetitions and task repetitions but to differ for task alternations. Thus, mean RT on cue repetition trials can be modeled as

$$RT = RT_{Baserep} + \mu_r \cdot \exp(-SOA/\mu_r), \qquad (4)$$

mean RT on task repetition trials as

$$RT = RT_{Baserep} + \mu_a \cdot \exp(-SOA/\mu_a), \qquad (5)$$

and mean RT on task alternation trials as

$$RT = RT_{Basealt} + \mu_a \cdot \exp(-SOA/\mu_a). \qquad (6)$$

$RT_{Baserep}$ and $RT_{Basealt}$ represent the time to process the target when the task is repeated or alternated, respec-

tively, and $RT_{Baserep} < RT_{Basealt}$. μ_r and μ_a represent the time to encode the cue when the cue is repeated or alternated, respectively, and $\mu_r < \mu_a$. Model 2 is nested within Model 3, because if $RT_{Baserep}$ and $RT_{Basealt}$ are constrained to be equivalent, Equations 4–6 are equivalent to Equations 1 and 2.

METHOD

Subjects

The subjects were 128 students from undergraduate psychology courses, who participated for partial fulfillment of course requirements. All the subjects reported normal or corrected-to-normal vision and were native speakers of English.

Design

The basic design included one between-subjects factor and three within-subjects factors: 4 (between subjects, target set size: 8, 16, 32, or 640) × 3 (task transition condition: cue repetition, task repetition, or task alternation) × 10 (SOA: 0, 100, 200, 300, 400, 500, 600, 700, 800, or 900) × 2 (response-to-cue interval, RCI: 100 or 600). We manipulated RCI as well as SOA so that SOA would not be confounded with the interval between the response and the next target. Following previous researchers (Logan & Bundesen, 2003; Logan & Zbrodoff, 1982; Meiran, 1996; Meiran, Chorev, & Sapir, 2000), the manipulation of RCI allowed us to interpret SOA as reflecting preparatory processes (cue encoding and set switching) and to rule out interpretations in terms of decay of past task sets (e.g., Allport, Styles, & Hsieh, 1994; Allport & Wylie, 2000).

Apparatus and Stimuli

Stimulus presentation and response recording were controlled by E-Prime 1.1 software running on a Dell Dimension computer with a Trinitron screen. Both targets and cues were presented in black lowercase Times New Roman font on a white background. The cues ranged from 17 to 70 mm in width, and the targets ranged from 10 to 63 mm. Word height was approximately 7 mm. The cues were presented just above the center of the display, and the targets were presented 10 mm below the cue. Viewing distance was not controlled. However, the subjects were positioned so as to be approximately 60 cm from the screen. At this distance, 1 cm is approximately 1° of visual angle. The timing between the presentations of the cue and the target varied between 0 and 900 msec in steps of 100 msec. Both the cue and the target remained on the screen until a response was made. Then the screen remained blank during the RCI of 100 or 600 msec.

A list of 640 target words was developed, drawn partially from Shoben, Cech, Schwanenflugel, and Sailor (1989) and supplemented by additional words chosen to complete the cells in the 2 × 2 crossing of origin × size tasks and to equate the cells in terms of word length and frequency. The word length ranged from 2 to 12 letters and averaged 6.46 and 6.25 for small and large items and 6.22 and 6.49 for living and nonliving items, respectively. The word frequency ranged from 0 to 117 per million and averaged 5.73 and 6.55 for small and large items and 5.62 and 6.65 for living and nonliving items, respectively (Kučera & Francis, 1967). These values did not differ significantly. Thirty-two targets were selected from the complete list in such a way that they matched the general characteristics of word length and frequency of the full list. Each of the 32 words was used in the 32-target condition. For the 16-target condition, the 32 words were divided into two sublists. For the 8-target condition, the 32 words were divided into four sublists. The subjects in these conditions saw targets from only one of the sublists.

Procedure

A four-cue/two-task explicit task-cuing procedure was used. A cue appeared prior to the onset of each target stimulus, indicating
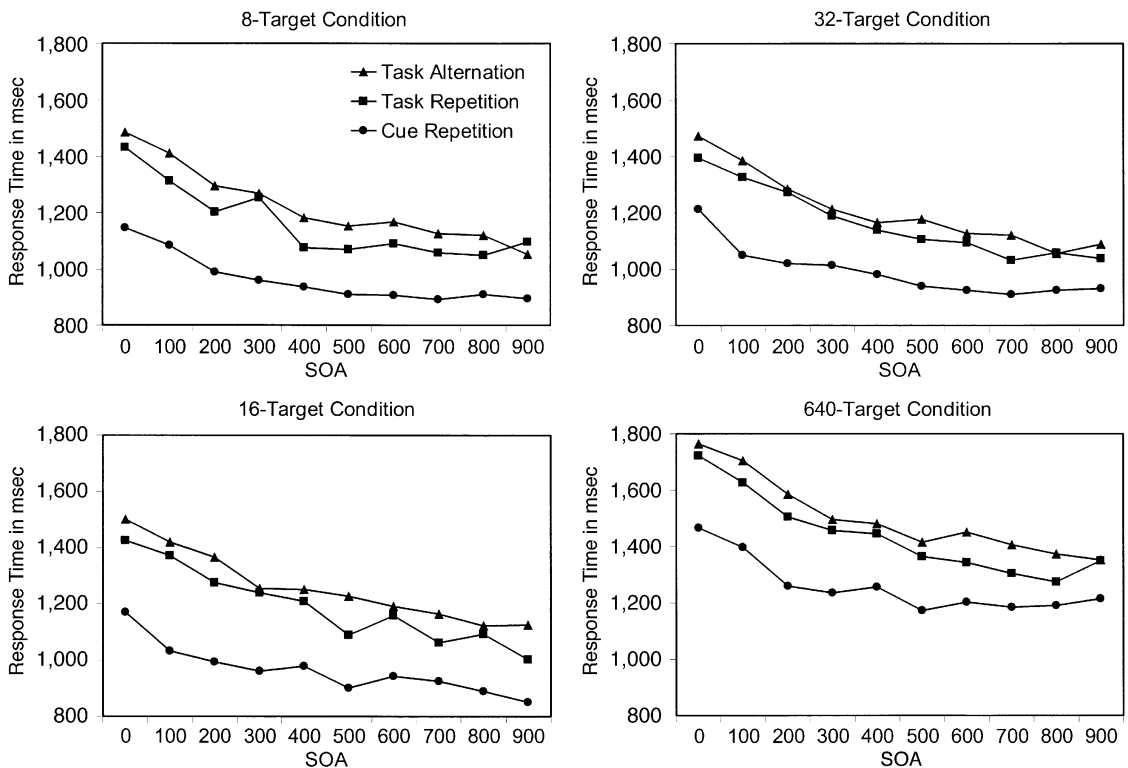
Figure 1. Mean response times as functions of stimulus onset asynchrony (SOA) in cue repetition (circles), task repetition (squares), and task alternation (triangles) conditions collapsed across response-to-cue interval for the 8-, 16-, 32-, and 640-target set size conditions.

which of the two semantic judgments was to be performed. The order of presentation of the four cues was random. Following a variable SOA, the target word appeared. The SOA varied randomly within blocks and ranged from 0 to 900 msec in 100-msec intervals. The subjects responded manually using the "z" and "/" keys on the computer keyboard. Specific mappings of stimulus value to left- versus right-hand responses were counterbalanced across subjects. For cues that used response labels (e.g., "living nonliving" or "large small"), the order of the words in the cue was manipulated to match the spatial configuration of the appropriate response. Following the response, the cue and target disappeared from the display, which remained blank during the RCI of either 100 or 600 msec.

The subjects received written and spoken instructions describing the types of judgments that they would be performing and the responses for each task. They were told to judge size relative to "something the size of a basketball or a goose." They were told that anything of plant or animal origin should be considered living. After receiving instructions, the subjects completed four blocks of 160 trials each, with self-paced breaks provided between blocks.

RESULTS

The first response of each block was removed, since it could not be categorized into a task transition condition. Trials were then sorted into task transition conditions based on the task performed on trial n and trial $n - 1$, forming three conditions: cue repetition, task repetition, and task alternation. All RTs longer than 5,000 msec or shorter than 150 msec were removed, resulting in the re-

moval of 0.9% of the data. Mean RTs were calculated for each task transition condition × timing interval. Analyses of the RT data did not differ with inclusion or exclusion of error trials, and thus, error trials were included to increase cell size for each point in the time course functions that were modeled.

Standard Analyses of RT Time Course Data

Overall, RTs were shortest in the cue repetition condition ($M = 1,044$ msec), followed by the task repetition and task alternation conditions ($Ms = 1,241$ and $1,300$ msec, respectively). These results indicate that a large portion of the standard measure of switch costs (the difference between task alternations and cue repetitions) may be accounted for by cue encoding (the difference between task repetition and cue repetition, 197 msec), rather than by set switching (the difference between task alternation and task repetition, 59 msec). These results are in line with Logan and Bundesen's (2003, in press) results, where the largest portion of the switch costs can be attributed to a cue repetition benefit (but see Mayr & Kliegl, 2003). At issue in the present experiment is whether the task transition effect interacts with the manipulation of number of targets. The pattern of large cue-encoding effects and small set-switching effects held true across all four target set sizes. For the 8-, 16-, 32-, and 640-target conditions, cue-encoding benefits were

202, 227, 175, and 181 msec, and set-switching costs were 61, 70, 44, and 63 msec, respectively. The lack of an interaction between task transition condition and target set size rules out the possibility that the compound-stimulus strategy is based only on episodic memory, because an episodic memory strategy cannot account for the data in the 640-target condition. In the 640-target condition, the subjects must have used a compound-stimulus strategy based on semantic retrieval. However, the subjects were faster in the 8-, 16-, and 32-target conditions, in which the targets were repeated, than in the 640-target condition, in which all the targets were unique. Thus, when an episodic compound-stimulus strategy is available, subjects appear to use it. When the episodic strategy is not available, subjects seem to rely on the semantic strategy, if they can.

The RT data were entered into a 4 (target set size: 8, 16, 32, or 640) $\times$ 3 (task transition: cue repetition, task repetition, or task alternation) $\times$ 10 (SOA: 0, 100, 200, 300, 400, 500, 600, 700, 800, or 900 msec) $\times$ 2 (RCI: 100 or 600 msec) mixed-factors analysis of variance (ANOVA). The main effect of target set size was significant [$F(3,124) = 13.12$, $MS_e = 2,736,094.1$, $p < .01$]. Fisher's least significant difference comparisons showed that the subjects in the 640-target condition responded significantly more slowly than the subjects in the other three conditions, which did not differ from each other. The main effect of task transition condition was significant [$F(2,248) = 393.78$, $MS_e = 116,461.5$, $p < .01$]. Nonorthogonal contrasts showed that cue repetitions were significantly faster than task repetitions [$F(1,124) = 423.3$, $p < .01$], which were in turn significantly faster than task alternations [$F(1,124) = 38.96$, $p < .01$]. The time course function, shown separately for each stimulus list condition in Figure 1, is captured in the main effect of SOA [$F(9,1116) = 1,212.35$, $MS_e = 49,978.9$, $p < .01$], and the task transition $\times$ SOA interaction [$F(18,2232) = 4.91$, $MS_e = 49,222.5$, $p < .01$], both of which were significant. A simple interaction analysis showed that the overall interaction resulted from a decrease in the difference between the cue repetition and the task repetition with increasing SOA [$F(9,1116) = 6.44$, $p < .01$] and that the difference between task repetition and task alternation did not change with SOA [$F(9,1116) = 1.15$, $p > .1$]. Importantly for the present investigation, the three-way interaction between task transition, SOA, and target set size was not significant [$F(54,2232) = 0.67$], indicating that the time course functions were not affected by the number of target items to which the subjects were exposed. The effect of transition condition also interacted significantly with RCI [$F(2,248) = 28.39$, $MS_e = 46,646.7$, $p < .01$]. As RCI increased from 100 to 600 msec, RTs on cue repetition trials increased by 51 msec ($Ms = 1,019$ and 1,070 msec), whereas RTs on task repetition and task alternation trials decreased by 28 msec ($Ms = 1,255$ and 1,227 msec) and 26 msec ($Ms = 1,313$ and 1,287 msec), respectively. Thus, the cue-encoding benefit decreased with increasing RCI, but the set-switching cost remained

relatively constant (Mayr & Kliegl, 2003). Finally, the four-way interaction of stimulus list length, transition condition, SOA, and RCI was significant [$F(54,2232) = 1.52$, $MS_e = 42,311.7$, $p < .05$], but the pattern of this interaction does not suggest alternative interpretations of the lower order effects.

Model Fits to Time Course Functions and Task Transition Effects

We fit Models 2, 2+1, and 3 to the mean RT data for the 30 task transition $\times$ SOA conditions in each of the eight combinations of target set size and RCI, using the Solver routine in Microsoft Excel to minimize the root-mean-squared deviation (RMSD) between observed and predicted values. We fit both the mean RTs averaged across subjects for each condition and the mean RTs for each of the 32 subjects in each condition individually. In Model 2, which assumes a cue-encoding benefit for cue repetitions and no endogenous act of set switching, cue repetition was modeled with Equation 1, and task repetition and task alternation were modeled with Equation 2. Each fit involved three parameters: cue-encoding time for task repetitions (μ_r), cue-encoding time for task alternations (μ_a), and the time to encode and respond to the target (RT$_{Base}$). In Model 2+1, which assumes both a cue-encoding benefit for cue repetitions and an endogenous act of set switching that occurs during the SOA, cue repetition was modeled with Equation 1, task repetition was modeled with Equation 2, and task alternation was modeled with Equation 3. There were four parameters: cue-encoding time for cue repetitions (μ_r), cue-encoding time for task repetitions and task alternations (μ_a), task-switching time (μ_s), and the time to encode and respond to the target (RT$_{Base}$). In Model 3, which assumes a cue-encoding benefit for cue repetitions and a target-processing advantage for task repetitions, cue repetition was modeled with Equation 4, task repetition was modeled with Equation 5, and task alternation was modeled with Equation 6. There were four parameters: cue-encoding time for cue repetitions (μ_r), cue-encoding time for task repetitions and task alternations (μ_a), the time to encode and respond to the target on cue repetition and task repetition trials (RT$_{BaseRep}$), and the time to encode and respond to the target on task alternation trials (RT$_{BaseAlt}$). The parameter estimates for each of the models fit to the RTs averaged across subjects, the means and standard errors of the parameter estimates for the model fits to the individual RT data, and the measures of goodness of fit (RMSD and r, the correlation between observed and predicted values) are given in Tables 2–5 for the 8-, 16-, 32-, and 640-target conditions, respectively. The observed RTs in each of the fitted condition are given in Table 1. Interested readers can compare them with predicted values they calculate from the parameters in Tables 2–5.

Looking first at the fits to the average of the subjects' data, Model 2 provided reasonable fits between the observed and the predicted data for all eight combinations

Table 1
Means (Ms) and Standard Errors (SEs) for RTs (in Milliseconds) and Response Accuracies (RAs) for Each Target Set Size Condition, Separated by RCI and Stimulus Onset Asynchrony (SOA)

	SOA (msec)	100-msec RCI RT M	SE	RA	600-msec RCI RT M	SE	RA
		8-Target Condition					
Cue repetition	0	1,135	48	.939	1,158	53	.942
	100	1,107	47	.936	1,062	43	.925
	200	1,011	44	.930	971	54	.940
	300	901	52	.928	1,021	57	.927
	400	891	55	.937	981	48	.945
	500	875	43	.954	947	45	.938
	600	882	44	.981	932	57	.916
	700	889	41	.937	893	59	.920
	800	875	41	.930	945	54	.925
	900	841	46	.936	950	53	.923
Task repetition	0	1,459	60	.945	1,406	57	.920
	100	1,337	60	.900	1,292	64	.959
	200	1,216	61	.957	1,192	58	.936
	300	1,251	63	.959	1,255	62	.915
	400	1,115	58	.942	1,039	59	.950
	500	1,128	59	.901	1,015	54	.947
	600	1,086	61	.932	1,098	65	.955
	700	1,051	64	.940	1,066	53	.925
	800	1,028	56	.952	1,069	52	.933
	900	1,086	60	.890	1,110	57	.943
Task alternation	0	1,499	53	.920	1,469	55	.918
	100	1,415	58	.914	1,406	55	.915
	200	1,316	57	.915	1,275	54	.929
	300	1,265	45	.899	1,275	55	.913
	400	1,201	56	.934	1,163	59	.915
	500	1,138	49	.916	1,167	53	.929
	600	1,166	58	.909	1,168	54	.909
	700	1,135	51	.918	1,120	51	.909
	800	1,084	51	.926	1,158	53	.924
	900	1,061	49	.920	1,044	50	.921
		16-Target Condition					
Cue repetition	0	1,111	48	.965	1,232	53	.953
	100	1,015	47	.945	1,056	43	.927
	200	959	44	.931	1,028	54	.940
	300	966	52	.951	958	57	.914
	400	981	55	.925	977	48	.905
	500	877	43	.907	928	45	.927
	600	926	44	.953	964	57	.950
	700	831	41	.937	1,023	59	.892
	800	851	41	.937	927	54	.939
	900	813	46	.924	891	53	.943
Task repetition	0	1,472	60	.904	1,377	57	.941
	100	1,395	60	.949	1,349	64	.896
	200	1,331	61	.890	1,224	58	.933
	300	1,217	63	.946	1,264	62	.944
	400	1,191	58	.906	1,227	59	.948
	500	1,103	59	.939	1,077	54	.935
	600	1,192	61	.928	1,127	65	.924
	700	1,010	64	.956	1,115	53	.916
	800	1,057	56	.921	1,130	52	.938
	900	1,411	60	.934	1,069	57	.927
Task alternation	0	1,538	53	.903	1,461	55	.904
	100	1,450	58	.940	1,393	55	.911
	200	1,402	57	.928	1,328	54	.916
	300	1,213	45	.918	1,299	55	.908
	400	1,290	56	.909	1,213	59	.910
	500	1,241	49	.925	1,213	53	.930
	600	1,188	58	.894	1,197	54	.921
	700	1,198	51	.906	1,130	51	.911
	800	1,118	51	.920	1,127	53	.916
	900	1,151	50	.912	1,103	50	.923

	SOA (msec)	100-msec RCI RT M	SE	RA	600-msec RCI RT M	SE	RA
		32-Target Condition					
Cue repetition	0	1,228	48	.936	1,202	53	.932
	100	1,042	47	.956	1,057	43	.969
	200	954	44	.932	1,088	54	.937
	300	1,007	52	.940	1,019	57	.962
	400	966	55	.956	996	48	.915
	500	937	43	.953	945	45	.950
	600	841	44	.919	1,008	57	.970
	700	863	41	.948	958	59	.930
	800	875	41	.926	975	54	.934
	900	909	46	.960	952	53	.964
Task repetition	0	1,429	60	.954	1,361	57	.937
	100	1,346	60	.945	1,309	64	.936
	200	1,287	61	.917	1,257	58	.945
	300	1,213	63	.942	1,169	62	.958
	400	1,132	58	.943	1,146	59	.940
	500	1,119	59	.948	1,097	54	.930
	600	1,090	61	.946	1,102	65	.949
	700	1,097	64	.951	966	53	.944
	800	1,039	56	.967	1,078	52	.955
	900	1,077	60	.958	997	57	.921
Task alternation	0	1,529	53	.925	1,417	55	.935
	100	1,426	58	.928	1,346	55	.910
	200	1,318	57	.932	1,251	54	.939
	300	1,222	45	.922	1,209	55	.914
	400	1,170	56	.922	1,165	59	.934
	500	1,207	49	.919	1,151	53	.908
	600	1,161	58	.927	1,091	54	.919
	700	1,124	51	.920	1,118	51	.942
	800	1,066	51	.931	1,047	53	.911
	900	1,097	50	.932	1,080	50	.915
		640-Target Condition					
Cue repetition	0	1,417	48	.931	1,515	53	.913
	100	1,335	47	.930	1,458	43	.959
	200	1,273	44	.899	1,244	54	.964
	300	1,229	52	.939	1,246	57	.866
	400	1,271	55	.949	1,241	48	.923
	500	1,170	43	.957	1,173	45	.948
	600	1,166	44	.936	1,240	57	.922
	700	1,185	41	.952	1,184	59	.912
	800	1,188	41	.925	1,191	54	.918
	900	1,154	46	.914	1,274	53	.935
Task repetition	0	1,692	60	.974	1,753	57	.927
	100	1,685	60	.953	1,570	64	.955
	200	1,514	61	.946	1,492	58	.901
	300	1,577	63	.924	1,338	62	.915
	400	1,466	58	.933	1,423	59	.951
	500	1,429	59	.937	1,297	54	.924
	600	1,390	61	.920	1,297	65	.925
	700	1,278	64	.942	1,332	53	.937
	800	1,295	56	.933	1,253	52	.924
	900	1,372	60	.907	1,328	57	.928
Task alternation	0	1,781	53	.926	1,750	55	.911
	100	1,803	58	.903	1,606	55	.908
	200	1,613	57	.917	1,555	54	.913
	300	1,515	45	.942	1,478	55	.926
	400	1,453	56	.921	1,508	59	.926
	500	1,428	49	.933	1,400	53	.924
	600	1,488	58	.907	1,411	54	.920
	700	1,404	51	.917	1,410	51	.930
	800	1,353	51	.942	1,391	53	.943
	900	1,312	50	.911	1,390	50	.917

Table 2
Values of the Best-Fitting Parameters and Measures of Goodness of Fit for Fits of Model 2, Model 2+1, and Model 3 to the Data Averaged Across Subjects, Means, and Standard Errors (SEs) of Values of Best-Fitting Parameters, and Measures of Goodness of Fit for Fits of the Same Models to 32 Individual Subjects in the 8-Target Condition

					Model 2			
RCI 100	μ_r	μ_a	μ_s	$RT_{BaseRep}$	RT_{Base}	$RT_{BaseAlt}$	r	RMSD
Average	262	615			868		.973	41
Mean	272	630			846		.678	187
SE	31	41			32		.028	11
					Model 2+1			
	μ_r	μ_a	μ_s	$RT_{BaseRep}$	RT_{Base}	$RT_{BaseAlt}$	r	RMSD
Average	257	585	67		872		.978	37
Mean	268	583	102		849		.696	182
SE	30	39	19		32		.026	10
					Model 3			
	μ_r	μ_a	μ_s	$RT_{BaseRep}$	RT_{Base}	$RT_{BaseAlt}$	r	RMSD
Average	268	584		864		924	.983	33
Mean	295	611		832		890	.709	180
SE	31	40		32		34	.025	10
					Model 2			
RCI 600	μ_r	μ_a	μ_s	$RT_{BaseRep}$	RT_{Base}	$RT_{BaseAlt}$	r	RMSD
Average	178	486			955		.932	54
Mean	230	538			902		.577	201
SE	43	44			52		.027	10
					Model 2+1			
	μ_r	μ_a	μ_s	$RT_{BaseRep}$	RT_{Base}	$RT_{BaseAlt}$	r	RMSD
Average	171	440	106		960		.948	48
Mean	223	476	122		909		.577	196
SE	41	45	24		50		.027	10
					Model 3			
	μ_r	μ_a	μ_s	$RT_{BaseRep}$	RT_{Base}	$RT_{BaseAlt}$	r	RMSD
Average	188	445		948		1,027	.958	43
Mean	245	499		891		970	.614	194
SE	45	47		53		60	.026	10

Note—RCI, response-to-cue interval.

of target set size and RCI. Averaged across target set size and RCI, the mean r value was .954 and the mean RMSD was 48 msec. This result reflects the fact that the cue-encoding benefit is considerably larger than the set-switching cost and is consistent with the compound-stimulus strategy. Model 2+1 fit the data slightly better than did Model 2. Averaged across target set size and RCI, the mean r value was .962, and the mean RMSD was 44 msec. Since Model 2 is nested within Model 2+1, the improvement in goodness of fit can be assessed by statistically comparing the correlation coefficients. Comparisons of goodness of fit showed modest improvements of Model 2+1 over Model 2 that did not reach significance in all combinations of target set size and RCI [8-target condition, $Fs(1,26) = 6.11$ and 8.88, $p < .05$; 16-target condition, $F(1,26) = 6.89$, $p < .05$ and $F(1,26) = 3.54$, $p > .05$; 32-target condition, $F(1,26) = 5.19$, $p < .05$ and $F(1,26) = 3.79$, $p > .05$; 640-target conditions, $Fs(1,26) = 5.62$ and 4.91, $p < .05$, for short and long RCI conditions, respectively].

Model 3 fit the data slightly better than did Model 2. Averaged across target set size and RCI, the mean r value was .969, and the mean RMSD was 39 msec. Model 2 is nested in Model 3, so the improvement in goodness of fit can be tested statistically. The improvements in goodness of fit over Model 2 were significant for all target set size × RCI conditions [8-target condition, $Fs(1,26) = 14.45$ and 17.42, $ps < .05$; 16-target condition, $Fs(1,26) = 20.47$ and 11.31, $ps < .05$; 32-target condition, $Fs(1,26) = 10.52$ and 11.63, $ps < .05$; 640-target conditions, $Fs(1,26) = 5.73$ and 18.01, $ps < .05$, for short and long RCI conditions, respectively]. Whereas Model 3 provided significantly better fits to the data than did Model 2, the parameters, $RT_{BaseRep}$ and $RT_{BaseAlt}$, which allow for residual switch costs in Model 3, differed by amounts that were relatively small, as compared with the differences between μ_r and μ_a.

The models did not fit the individual subject data as well as the average data, but the quantitative relationships among the three models were the same as those for

Table 3
Values of the Best-Fitting Parameters and Measures of Goodness of Fit for Fits of Model 2, Model 2+1, and Model 3 to the Data Averaged Across Subjects, Means, and Standard Errors (*SE*s) of Values of Best-Fitting Parameters, and Measures of Goodness of Fit for Fits of the Same Models to 32 Individual Subjects in the 16-Target Condition

					Model 2			
RCI 100	μ_r	μ_a	μ_s	$RT_{BaseRep}$	RT_{Base}	$RT_{BaseAlt}$	r	RMSD
Average	253	665			862		.958	57
Mean	270	690			834		.697	201
SE	33	42			33		.022	13
					Model 2+1			
	μ_r	μ_a	μ_s	$RT_{BaseRep}$	RT_{Base}	$RT_{BaseAlt}$	r	RMSD
Average	249	626	95		865		.967	51
Mean	260	627	126		842		.720	194
SE	30	39	25		32		.022	12
					Model 3			
	μ_r	μ_a	μ_s	$RT_{BaseRep}$	RT_{Base}	$RT_{BaseAlt}$	r	RMSD
Average	263	619		855		947	.977	42
Mean	280	643		826		917	.726	193
SE	34	42		34		41	.022	12
					Model 2			
RCI 600	μ_r	μ_a	μ_s	$RT_{BaseRep}$	RT_{Base}	$RT_{BaseAlt}$	r	RMSD
Average	197	519			962		.948	48
Mean	225	547			930		.592	201
SE	30	36			37		.024	13
					Model 2+1			
	μ_r	μ_a	μ_s	$RT_{BaseRep}$	RT_{Base}	$RT_{BaseAlt}$	r	RMSD
Average	193	493	62		965		.954	46
Mean	221	483	117		934		.592	197
SE	30	43	25		38		.024	12
					Model 3			
	μ_r	μ_a	μ_s	$RT_{BaseRep}$	RT_{Base}	$RT_{BaseAlt}$	r	RMSD
Average	203	485		958		1,020	.963	41
Mean	235	508		923		984	.628	195
SE	30	43		38		46	.021	12

Note—RCI, response-to-cue interval.

the fits to the average data. For Model 2, the mean *r* value was .63, and the mean RMSD was 198 msec, averaged over subjects, target set size, and RCI. For Model 2+1, the corresponding means were .64 and 193 msec. For Model 3, the corresponding means were .66 and 191 msec. The fit of Model 2 can again be directly compared with those of the other two models in which it is nested. The top panel in Table 6 gives the number of subjects who showed significant increases in model fit from Model 2 to the other models. At the level of individual subjects, very few subjects showed a significant improvement in fit between Model 2 and Models 2+1 and 3.[2]

Models 2+1 and 3 cannot be compared directly, since the models are not nested. However, we can compare the number of subjects for which the *r* value for one model exceeded that for the other, using the normal approximation to the binomial distribution. Correlation coefficients were larger for Model 3 than for Model 2+1 in a significant number of subjects in all conditions, except for the 16-target, 100-msec RCI and the 32-target, 600-msec RCI conditions. This finding indicates that the small differences between task repetition and task alternation conditions are best accounted for by a process that occurs following the onset of the target, rather than during the SOA.

Whereas the overall fits for all the models were significantly poorer when fit to the individual subject data than when fit to the average means across subjects, the parameter estimates were similar. Most of the parameter estimates for the fits to average means were within the 95% confidence intervals of the mean parameter estimates of the fits to individual subject data. However, for Model 2+1, the estimates of μ_s based on the average means across subjects were below the 95% confidence intervals for the mean parameter estimates of the fits to individual subject data for the 16-target condition at the 600-msec RCI and the 32-target condition at both RCIs.

Ancillary RT Analyses

In addition to the primary analyses of the time course functions, the experimental design allows us to consider several other factors that may impact subjects' respond-

Table 4
Values of the Best-Fitting Parameters and Measures of Goodness of Fit for Fits of
Model 2, Model 2+1, and Model 3 to the Data Averaged Across Subjects, Means, and
Standard Errors (*SEs*) of Values of Best-Fitting Parameters, and Measures of Goodness
of Fit for Fits of the Same Models to 32 Individual Subjects in the 32-Target Condition

					Model 2			
RCI 100	μ_r	μ_a	μ_s	$RT_{BaseRep}$	RT_{Base}	$RT_{BaseAlt}$	r	RMSD
Average	262	595			890		.968	43
Mean	308	649			835		.707	172
SE	50	54			4		.024	12
					Model 2+1			
	μ_r	μ_a	μ_s	$RT_{BaseRep}$	RT_{Base}	$RT_{BaseAlt}$	r	RMSD
Average	256	565	66		895		.973	40
Mean	302	600	101		841		.724	168
SE	50	57	16		46		.024	12
					Model 3			
	μ_r	μ_a	μ_s	$RT_{BaseRep}$	RT_{Base}	$RT_{BaseAlt}$	r	RMSD
Average	268	566		886		942	.977	36
Mean	318	622		829		884	.727	167
SE	48	55		45		49	.024	12
					Model 2			
RCI 600	μ_r	μ_a	μ_s	$RT_{BaseRep}$	RT_{Base}	$RT_{BaseAlt}$	r	RMSD
Average	210	444			969		.968	32
Mean	268	493			917		.604	175
SE	40	43			37		.030	11
					Model 2+1			
	μ_r	μ_a	μ_s	$RT_{BaseRep}$	RT_{Base}	$RT_{BaseAlt}$	r	RMSD
Average	206	425	46		971		.971	30
Mean	263	440	101		921		.604	171
SE	40	47	21		37		.030	11
					Model 3			
	μ_r	μ_a	μ_s	$RT_{BaseRep}$	RT_{Base}	$RT_{BaseAlt}$	r	RMSD
Average	219	426		962		1,003	.977	27
Mean	282	479		905		948	.628	171
SE	41	45		36		42	.029	11

Note—RCI, response-to-cue interval.

ing differently on different types of task transitions. The cues used in the present experiment were either name cues (i.e., "origin" and "size") or mapping cues (i.e., "living nonliving" and "large small"). Mayr and Kliegl (2000) demonstrated that name cues result in larger switch costs than do mapping cues that directly indicate the category-to-response mapping. We considered the effect of name versus mapping cues in a 4 (target set size: 8, 16, 32, or 640) × 3 (task transition: cue repetition, task repetition, or task alternation) × 2 (cue type: name or mapping) mixed-factors ANOVA, collapsing across SOA and RCI in order to have an adequate number of data points in each cell. The interaction of task transition and cue type was significant [$F(2,248) = 4.15$, $MS_e = 5,224.5$, $p < .05$]. Planned comparisons of name and mapping cues showed that RTs were significantly shorter for mapping cues than for name cues, by 40 msec for task repetitions and 27 msec for task alternations. For the cue repetitions, mapping cues were only 4 msec faster than name cues, which was not significant. This

result suggests that the difference between name and mapping cues acts at the level of cue encoding, rather than changes in task.

The responses in this experiment were bivalent, with the same two keys mapped to responses for both tasks. Consequently, it was possible to analyze the effects of response repetitions on task transitions. Previous researchers have shown that response repetitions benefit performance when a task repeats but interfere when the task switches (Mayr & Kliegl, 2003; Rogers & Monsell, 1995). We analyzed response repetitions in a 4 (target set size: 8, 16, 32, or 640) × 3 (task transition: cue repetition, task repetition, or task alternation) × 2 (response transition: repetition or alternation) mixed-factors ANOVA, collapsing across SOA and RCI. The interaction of task transition and response transition was significant [$F(2,248) = 28.73$, $MS_e = 4,599.6$, $p < .01$]. Planned comparisons of the response transition effect showed that, as compared with response alternations, RTs were 54 msec shorter on response repetitions for cue

Table 5
**Values of the Best-Fitting Parameters and Measures of Goodness of Fit for Fits of
Model 2, Model 2+1, and Model 3 to the Data Averaged Across Subjects, Means, and
Standard Errors (*SE*s) of Values of Best-Fitting Parameters, and Measures of Goodness
of Fit for Fits of the Same Models to 32 Individual Subjects in the 640-Target Condition**

	μ_r	μ_a	μ_s	$RT_{BaseRep}$	RT_{Base}	$RT_{BaseAlt}$	r	RMSD
				Model 2				
RCI 100								
Average	244	605			1,170		.967	45
Mean	262	635			1,140		.639	212
SE	33	27			39		.024	10
				Model 2+1				
Average	237	572	72		1,175		.973	41
Mean	253	581	106		1,146		.661	206
SE	33	29	24		39		.025	10
				Model 3				
Average	251	582		1,166		1,212	.973	41
Mean	266	610		1,136		1,184	.663	205
SE	34	28		39		46	.025	10
				Model 2				
RCI 600								
Average	245	491			1,213		.921	60
Mean	280	544			1,164		.548	230
SE	38	36			33		.021	12
				Model 2+1				
Average	240	452	94		1,217		.932	55
Mean	281	482	127		1,166		.548	224
SE	37	39	29		33		.021	11
				Model 3				
Average	260	450		1,202		1,289	.951	47
Mean	294	504		1,155		1,238	.585	221
SE	38	35		32		47	.021	11

Note—RCI, response-to-cue interval.

repetition trials, RTs were 36 msec longer on response repetitions for task alternation trials, and RTs were a nonsignificant 6 msec longer on response repetitions for task repetition trials. Response repetitions provide a benefit when both the cue and the task repeat and a cost when both the cue and the task change. The task repetition condition, in which no response repetition effect is seen, may represent a balance of these two influences. This pattern of results fails to replicate the findings of Mayr and Kliegl (2003), who found benefits for response repetitions in both cue repetition and task repetition conditions.

Table 6
Comparisons of Model Fits to Data From Individual Subjects

	8 Targets		16 Targets		32 Targets		640 Targets	
	100	600	100	600	100	600	100	600
Number of Subjects Showing Significant Improvement in Fit								
Model 2 vs. Model 2+1	4	4	5	3	3	3	5	3
Model 2 vs. Model 3	6	5	5	6	5	2	7	5
Number of Subjects Showing Absolute Improvement in Fit								
Model 2+1 vs. Model 3	26	24	20*	25	22	17*	23	24

Note—100, 600 are response-to-cue intervals in milliseconds.   *Values do not differ from those expected if fit values for the models varied at chance.

Accuracy Analyses

Response accuracies for each task transition × SOA condition separated by target set size and RCI are shown in Table 1. Response accuracy did not vary as a function of target set size (Ms = .929, .926, .938, and .928 for the 8-, 16-, 32-, and 640-target conditions, respectively). Task transition did affect accuracy [$F(2,248) = 26.45$, $MS_e = 0.008, p < .01$]. Accuracy was higher for cue repetitions ($M = .936$) and task repetitions ($M = .935$) than for task alternations ($M = .920$). Planned contrasts showed that the task alternations differed significantly from the task repetition and the cue repetition conditions, which did not differ from each other.

DISCUSSION

In a four-cue/two-task explicit-cuing procedure, cue repetitions were substantially faster than task repetitions, which were in turn slightly faster than task alternations. This pattern of results suggests that a large portion of the standard switch costs measured using the explicit task-cuing procedure can be accounted for by a cue-encoding benefit on repetition trials, as compared with alternation trials. This finding is directly contrary to the modal interpretation of results from explicit task-cuing experiments, which interprets the difference between repetitions and alternations as reflecting the time required to perform an endogenous act of set switching when the task switches. Instead, these data are consistent with performance based on a compound-stimulus strategy (Logan & Bundesen, 2003, in press).

The primary question addressed in the present experiment was whether the compound-stimulus strategy is implemented through episodic memory retrieval of previously experienced cue–target pairs or through semantic memory retrieval based on a compound retrieval cue provide by the cue–target pair. Critical to answering this question, the pattern of task transition effects was constant across all four target set sizes. The difference between task repetition and task alternation was the same when every target in the experiment was unique (the 640-target condition) as when the targets repeated (the 8-, 16-, and 32-target conditions). Thus, it must be possible to implement the compound-stimulus strategy with a semantic memory retrieval process. Subjects do not use the compound-stimulus strategy only when they have had multiple repetitions of a cue–target pair and, thus, can retrieve a response based on relatively uninterpreted stimuli from episodic memory. They also use the compound-stimulus strategy to retrieve information from semantic memory. In addition, there is evidence that subjects also use an episodic compound-stimulus strategy when the repetition of cue–target pairs within the experiment makes this strategy available. Overall RTs and estimates of the RT$_{Base}$ parameters for the different models were all shorter in the 8-, 16-, and 32-target conditions, in which targets were repeated, than in the 640-target condition, in which every target was unique. We suggest that

this speed-up is due to retrieval from episodic memory (Logan, 1988).

Although the largest part of the difference in RTs between task transition conditions can be attributed to cue-encoding benefits when the cue repeats, there was a small but consistent difference between the task repetition and the task alternation conditions. There are several possible interpretations of this effect. First, the difference may reflect a cost that occurs on every task alternation trial and reflects the time necessary to carry out an endogenous act of set switching. This interpretation would be in line with the standard view that the explicit task-cuing procedure captures executive control processes engaged in reconfiguring task set or with Mayr and Kliegl's (2003) revision of this view, which claims that both cue encoding and task switching affect the difference between repetitions and alternations. However, the 59-msec difference may be unrealistically small to account for a complex process of reconfiguration (see also Logan & Bundesen, 2003, in press). Second, the difference between task repetition and task alternation conditions may reflect a relatively long set-switching process that occurs on a small percentage of trials. The compound-stimulus strategy may be used on most of the trials. If executive processes are engaged only in a subset of trials, the explicit task-cuing procedure may not be an efficient method for studying executive control processes involved in task switching. Alternatively, the difference between task repetitions and task alternations may be accounted for within the compound-stimulus strategy without hypothesizing an additional act of set switching. In the task repetition condition, the cues on trial n and trial $n − 1$ (e.g., "size" and "large small") are related semantically. Thus, the cue on the current trial may be primed by the semantically related cue on the previous trial, and this may speed up the cue-encoding process.

For researchers wanting to study executive control processes using task-switching procedures, it is discouraging to consider the possibility that the switch cost measure in this popular technique may not reflect an endogenous act of control. However, there may well be conditions under which endogenous acts of control are brought to bear on task performance and may be measured accurately. The use of the compound-stimulus strategy, instead of an endogenous act of control, may depend on the nature of the tasks being performed. Semantic categorizations of words, as in the present experiment, or categorizations of digits, as in Logan and Bundesen (2003, in press), involve stimuli with which subjects are familiar from contexts outside of the experiment. No learning has to take place during the experiment in order for these tasks to be performed. The tasks can be performed simply with the same semantic memory retrieval strategy. No endogenous act of task set reconfiguration is necessary. However, there may well be tasks for which applying a specialized task set configuration is necessary. For example, tasks that involve judgments of different perceptual di-

mensions may well benefit from having attentional control settings (Folk, Remington, & Johnston, 1992) or attention weights tuned to the currently relevant task dimension (e.g., Arrington, 2002; Arrington et al., 2003). When these tasks are presented in a task-switching experiment, subjects may well use a strategy that involves performing an endogenous act of set switching that is reflected in measures of switch costs (Arrington et al., 2003). Thus, Mayr and Kliegl (2003) may have found larger differences between task repetition and task alternation conditions than have been shown in the present experiment or in Logan and Bundesen's experiments because their tasks involved switching between perceptual dimensions of shape and color (but see Logan & Bundesen, in press). Researchers using the explicit task-cuing procedure should pay careful attention to the individual tasks and the cognitive operations involved in carrying out these tasks when addressing questions of how control processes might be involved in switching from one task to another. Since task-switching experiments generally focus on the executive processes that carry out task switching, rather than on the subordinate level processes that carry out individual tasks (Logan & Gordon, 2001), relatively little attention has been paid to the effects that different tasks have on the executive processes involved in task switching (but see Arrington, 2002; Arrington et al., 2003).

CONCLUSION

The explicit task-cuing procedure has been widely used to study the executive control process of task switching. However, the present results highlight the possibility that the standard switch cost measure derived from this procedure may result more from a cue-encoding benefit when the task repeats than from a cost associated with switching sets when the task changes. Subjects appear to use compound-stimulus strategies, in which the cue and the target act jointly to retrieve responses from episodic and semantic memory. The present results suggest that researchers must come to understand the conditions under which task switching does and does not require an endogenous act of control, if they hope to separate the role of the executive from those of the subordinate processes.

REFERENCES

Allport, A., Styles, E. A., & Hsieh, S. (1994). Shifting intentional set: Exploring the dynamic control of tasks. In C. Umiltà & M. Moscovitch (Eds.), *Attention and performance XV: Conscious and nonconscious information processing* (pp. 421-452). Cambridge: MA: MIT Press.

Allport, A., & Wylie, G. (2000). Task switching, stimulus–response bindings, and negative priming. In S. Monsell & J. Driver (Eds.), *Attention and performance XVIII: Control of cognitive processes* (pp. 35-70). Cambridge, MA: MIT Press.

Altmann, E. M. (2002). Functional decay of memory for tasks. *Psychological Research*, **66**, 287-297.

Arrington, C. M. (2002). *Explorations in task space: Similarity effects on task switching*. Unpublished doctoral dissertation, Michigan State University.

Arrington, C. M., Altmann, E. M., & Carr, T. H. (2003). Tasks of a feather flock together: Similarity effects in task switching. *Memory & Cognition*, **31**, 781-789.

Arrington, C. M., & Logan, G. D. (2004). The cost of a voluntary task switch. *Psychological Science*, **15**, 610-615.

Folk, C. L., Remington, R. W., & Johnston, J. C. (1992). Involuntary covert orienting is contingent on attentional control settings. *Journal of Experimental Psychology: Human Perception & Performance*, **18**, 1030-1044.

Kučera, H., & Francis, W. N. (1967). *Computational analysis of present-day American English*. Providence, RI: Brown University Press.

Logan, G. D. (1985). Executive control of thought and action. *Acta Psychologica*, **60**, 193-210.

Logan, G. D. (1988). Toward an instance theory of automatization. *Psychological Review*, **95**, 492-527.

Logan, G. D., & Bundesen, C. (2003). Clever homunculus: Is there an endogenous act of control in the explicit task cuing procedure? *Journal of Experimental Psychology: Human Perception & Performance*, **29**, 575-599.

Logan, G. D., & Bundesen, C. (in press). Very clever homunculus: Compound stimulus strategies for the explicit task-cuing procedure. *Psychonomic Bulletin & Review*.

Logan, G. D., & Gordon, R. D. (2001). Executive control of visual attention in dual-task situations. *Psychological Review*, **108**, 393-434.

Logan, G. D., & Zbrodoff, N. J. (1982). Constraints on strategy construction in a speeded discrimination task. *Journal of Experimental Psychology: Human Perception & Performance*, **8**, 502-520.

Mayr, U., & Kliegl, R. (2000). Task-set switching and long-term memory retrieval. *Journal of Experimental Psychology: Learning, Memory, & Cognition*, **26**, 1124-1140.

Mayr, U., & Kliegl, R. (2003). Differential effects of cue changes and task changes on task-set selection costs. *Journal of Experimental Psychology: Learning, Memory, & Cognition*, **29**, 362-372.

Meiran, N. (1996). Reconfiguration of processing mode prior to task performance. *Journal of Experimental Psychology: Learning, Memory, & Cognition*, **22**, 1423-1442.

Meiran, N., Chorev, Z., & Sapir, A. (2000). Component processes in task switching. *Cognitive Psychology*, **41**, 211-253.

Meyer, D. E., & Kieras, D. E. (1997). A computational theory of executive cognitive processes and multiple-task performance: Pt. 1. Basic mechanisms. *Psychological Review*, **104**, 3-65.

Norman, D. A., & Shallice, T. (1986). Attention to action: Willed and automatic control of behavior. In R. J. Davidson, G. E. Schwartz, & D. Shapiro (Eds.), *Consciousness and self-regulation: Advances in research and theory* (Vol. 4, pp. 1-18). New York: Plenum.

Rogers, R. D., & Monsell, S. (1995). Costs of a predictable switch between simple cognitive tasks. *Journal of Experimental Psychology: General*, **124**, 207-231.

Rubinstein, J. S., Meyer, D. E., & Evans, J. E. (2001). Executive control of cognitive processes in task switching. *Journal of Experimental Psychology: Human Perception & Performance*, **27**, 763-797.

Shoben, E. J., Cech, C. G., Schwanenflugel, P. J., & Sailor, K. M. (1989). Serial position effects in comparative judgments. *Journal of Experimental Psychology: Human Perception & Performance*, **15**, 273-286.

Sudevan, P., & Taylor, D. A. (1987). The cuing and priming of cognitive operations. *Journal of Experimental Psychology: Human Perception & Performance*, **13**, 89-103.

Townsend, J. T., & Ashby, F. G. (1983). *Stochastic modeling of elementary psychological processes*. New York: Cambridge University Press.

NOTES

1. Logan and Bundesen's (2003) experiments differed from Mayr and Kliegl's (2003) experiments in terms of the stimuli, tasks, cues, and statistical contingencies between trials. Logan and Bundesen (in press) investigated the effect of the difference in cues. Logan and Bundesen (2003) used meaningful word cues (e.g., "magnitude" and "high–low" for magnitude judgments and "parity" and "odd–even" for parity judgments), whereas Mayr and Kliegl (2003) used arbitrary letters (e.g., G

and S for the color task and B and W for the form task). Logan and Bundesen (in press) compared meaningful word cues and arbitrary letter cues. They found no difference between task repetitions and task alternations with word cues, replicating Logan and Bundesen (2003). They found a substantial difference between task repetitions and task alternations with letter cues, replicating Mayr and Kliegl (2003). Unlike Mayr and Kliegl (2003), they interpreted the letter cue results in terms of an extended compound-stimulus strategy, in which subjects use task names as mediators. That is, subjects retrieve the task name associated with the letter cue and use that name and the target to retrieve the appropriate response. Logan and Bundesen (in press) suggested that task repetitions may be faster than task alternations because of facilitation from repeating the same mediator.

2. By contrast, when the comparison in goodness of fit was made between Model 2+1, which included both a cue-encoding benefit and a set-switching cost, and Model 1, which included only a set-switching cost, the numbers of subjects that showed a significant increase in fit ranged between 10 and 23 across the various target set size × RCI conditions. Thus, the small number of subjects that showed a significant improvement in fit for Models 2+1 and Model 3 over Model 2 did not reflect an inability to find significant differences in model fits at the level of individual subjects. Rather, it suggests that Models 2+1 and 3 did not provide a better fit than did Model 2 for most of the individual subjects' data.