Memory search instead of template matching? 
Representation-guided inference in same–different performance

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Data from two experiments using transformationally related patterns forming rotation/reflection equivalence sets of different size’s are presented. In a same–different experiment, two successively presented patterns were judged as same when they belonged to the same equivalence set, and different otherwise. Reaction times depended on the size of the equivalence set to which the patterns belong. This was the case, even when they were physically identical. Results are interpreted within a framework of memory-guided inference which assumes that participants perform a memory search within the equivalence sets activated by the compared patterns instead of comparing these directly. In Experiment 2, goodness ratings were required which are shown to reflect a second component of information processing.

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1. Memory search instead of template matching?

1.1. Representation-guided inference in same–different performance

The question of why and how reaction time (RT) in complex visual recognition varies as a function of stimulus material and task demand belongs to the basic issues of cognitive theory. Stimulus specificity of processing has been addressed over a long period of time within the framework of classification paradigms. In the sixties and early seventies the relations between format of representation in long-term memory
and specific modes of processing, such as visual-perceptual versus conceptual classification (Klatzky, 1972; Posner & Mitchell, 1967; Posner, Boies, Eichelmann, & Taylor, 1969) or prototype-based versus feature-based classification (Posner & Keele, 1968) were a major topic. Dependencies on task demand have primarily been addressed in the context of levels of conceptual representation (Rosch & Lloyd, 1978), whereas specific recognition strategies were part of the discussion on performance in item recognition (Sternberg, 1966) and in extensions of this task permitting usage of class information (e.g. Burrows & Okada, 1974; Naus, 1974). Formal work in this area focused on special strategy aspects such as those of serial versus parallel or exhaustive versus self-terminating processing (see Townsend & Van Zandt, 1990, or Van Zandt & Townsend, 1993, for a review). In general, until recently, material-related and demand-related determinants have rarely been studied systematically in their interaction as parts of integral processing architectures. This issue has been the focus of investigations within the heuristic framework of memory-guided inference, MGI (Buffart & Geissler, 1984; cf. also Geissler, 1983, 1987, 2001, 2002; Geissler & Lachmann, 1996, 1997; Lachmann, 2000, 2001; Lachmann & Geissler, 1999; Lachmann & van Leeuwen, 2002).

1.2. Memory-guided inference

A central tenet of the MGI approach implies that task demands enter into processing strategies via specific task-related framing of structured representations of object sets whereas the basic routines of processing themselves are supposed to be independent of the task. The underlying assumption is that classification performance is essentially controlled top-down by standardized reference to representations in memory. Specifications of this basic MGI rationale were successfully applied in modeling RT data for stimulus sets consisting of figures composed of highly distinctive parts in various specific tasks, e.g. serial-order detection (Geissler, Klix, & Scheidereiter, 1978), item-recognition (Geissler, Puffe, & Stern, 1982), and multiple naming and verification (Geissler & Puffe, 1983; see also Geissler & Buffart, 1985). In these instances, it was shown that processing can approximately be described, as in the classical item-recognition paradigm (Sternberg, 1966), by serial search strategies with the specificity that procedures are regularly found to be self-terminating and to include more than one stage of processing. Like any approach to classification performance, MGI predicts that common features or other common properties of objects are employed to reduce processing load.

However, besides other discrepancies in the detail, a striking difference from traditional accounts consists in the prediction of conditions in which the cognitive system is expected to be incapable of exempting redundant information from checking. According to MGI this phenomenon of seeming redundancy in processing (Geissler, 1985, 1995, 2001) should emerge in frequent cases in which representational rules do not permit explication of commonalties in task-related representations of object sets. For illustration of this notion, consider the simple example of four objects described by the combinations \((a_1, b_1), (a_1, b_2), (a_2, b_1),\) and \((a_2, b_2)\) of dimensionally ordered binary features to which the responses \(R_{11}, R_{12}, R_{21},\) and \(R_{22}\) are
assigned. In a traditional view, decision upon the correct response to be elicited can be made in two sequential steps of dichotomization deciding whether \( a_1 \) or \( a_2 \), \( b_1 \), or \( b_2 \) are present. From the point of view of MGI, however, such a procedure is untenable, because the expressions in parentheses are to be considered as separate representations of categories to which representations of the responses are uniquely attached. Consequently, in sequential processing, if no match would have been found for a category involving the checking of a certain feature, for example \( a_1 \), the same feature needs to be checked a second time if it reoccurs as a constituent of another category representation to be checked.

1.3. Group coding

Most of the MGI related work was carried out with material using combinations of elements from given sets of distinctive features. To explore the scope of the approach, it was tempting to consider stimulus sets generated by a different rule to see if the basic rationale applied to them as well. A particularly interesting case consists in tasks involving stimulus sets generated by what we will call transformational rules. An example represents a set of patterns like \( \triangle \square \triangle \triangle \) which can be considered as resulting from vertical and horizontal reflections of any one of the patterns. Consequently, only one of these patterns which serves as the prototype would have to be described in its full structure while the rest of the entire set can be coded by a sequence of transformation operations (such as rotation) applied to this prototype. Therefore, from the point of view of MGI, transformationally related sets of patterns should give rise to nested sets of representations playing the role of collective codes or group codes for these sets of patterns. Properties of these collective codes are thus expected to be important predictors of classification performance. This should be particularly true of the number of elements forming the sets, the so-called equivalence set size (ESS). Effects pointing to a strong influence of ESS have indeed been very well known in the literature since early goodness judgment studies of Garner and co-workers (Garner, 1962; Garner & Clement, 1963). It is a common finding that ESS also affects latencies under conditions that impose strong task-specific constraints. Robust ESS effects on RTs were, for example, found in multiple naming tasks employing arrays of black and white circles (Geissler, 1972, see Geissler, 2001 for review) or angular patterns (Geissler, 1980). The prominence of the effects is underlined by the fact that ESS as a measure of group size shows robust impact on RTs in these tasks, although the responses to be generated were specific to each of the single patterns presented.

For systematic exploration of recognition performance for transformationally related sets of objects, it is desirable to employ sets of patterns which are large enough to prevent idiosyncratic strategies and simultaneously decompose into well-defined subsets of different ESSs. Nearly ideal in this respect are the five-dot patterns first used by Garner and Clement (1963) which are constructed on an imaginary \( 3 \times 3 \) squared grid by leaving no row or column empty. Under reflections and rotations (so-called “R&R” operations, see Garner & Clement, 1963), ESSs of distinct subsets
of transformationally related patterns can assume exactly the three values 1, 4, and 8 (see Fig. 1). Using these pattern sets, effects of ESS on RT were, for instance, demonstrated by Clement and Vernadoe (1967) in a speeded classification task and by Checkosky and Whitlock (1973) in item-recognition. The results of these studies were controversially discussed (Pomerantz, 1977; see also Biederman, Hilton, & Hummel, 1994) in the context of the question about the role of ESS considered as a measure of pattern goodness (Garner, 1962).

Within another theoretical background, Schmidt and Ackermann (1990) showed an ESS effect in a same–different experiment. Both studies by Checkosky and Whitlock (1973) and Schmidt and Ackermann (1990) revealed additional effects of individual pattern properties for which no specific account was given. From the point of view of MGI, such effects are expected and reflect structural specificity of patterns within a given group code that distinguishes them from other patterns of the same ESS.

In this paper we will further elaborate upon the paradigm introduced by Schmidt and Ackermann (1990). The conditions employed in this study are of particular relevance for two main reasons. In contrast to former MGI-related investigations, the task does not involve categorization of one item per trial, but rather comparison of two items. An effect of ESS on RT under these conditions is not plausible from traditional models of matching. Thus, explanation of its emergence could be considered as a crucial test of an approach which is based upon the idea of representational guidance. Secondly, decisions about match or non-match in the task cannot be derived from information stored in long-term memory. Successful application of MGI under these circumstances would therefore imply that the approach can be expanded to short-term representations in working memory. Thus, application to the task could open an interesting new field of inquiry for the approach.

In their specific design Schmidt and Ackermann (1990) employed what they called a “categorical same–different task”. Two patterns were presented in succession with a short interval between them. Participants were to respond same when the patterns were identical irrespective of orientation, and different otherwise. A robust finding under these conditions is an increase of mean RT for positive decisions with the ESS of the group to which the patterns of a pair belong. As Schmidt and Ackermann noticed, this applies also to the subset of comparisons between physically identical patterns (i.e. patterns that agree in structure and in orientation). Note that this finding for comparisons which do not imply transformational distances obviously ex-

<table>
<thead>
<tr>
<th>ESS 1</th>
<th>ESS 4</th>
<th>ESS 8</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image" alt="Pattern Samples" /></td>
<td><img src="image" alt="Pattern Samples" /></td>
<td><img src="image" alt="Pattern Samples" /></td>
</tr>
</tbody>
</table>

Fig. 1. Pattern samples for the 17 subsets generated by R&R-operations (Garner & Clement, 1963). The samples represent the two subsets of set size one (left side), the eight subsets of set size four, and the seven subsets of set size eight (right side).
cludes any simple explanation in terms of mental rotation and reflection (Shepard & Metzler, 1971).

1.4. Search instead of direct comparison

There are two more specific findings of Schmidt and Ackermann’s (1990) study that provide mutually related cues for adequate modeling. The effect in pairs of physically identical patterns as a function of ESS proved to be closely linear. Secondly, if using a factor of 2 for ESS of categorically identical patterns (that is patterns related by rotations and or reflection), this linear trend extends throughout all positive decisions.

This linear relation is one of the arguments for the fundamental assertion on which the treatment of the same–different paradigm in the present paper is based. Namely, that ESS plays an analogous role for performance in our study as the size of the memorized item set in the classical item-recognition task for memory search (Sternberg, 1966). This view is supported by a reanalysis by Schmidt and Ackermann (1990) of Checkosky and Whitlock’s (1973) data. As Schmidt and Ackermann were able to show, mean RTs for intact and degraded stimuli in this task can be approximated by linear functions of equal slopes if plotted against the product of memory set size and the item-specific ESS values. This suggests that the role of both parameters in memory search is completely analogous. Contrary to item recognition, however, memory search is counterintuitive in a comparison task which according to intuition can be solved by a direct matching procedure which includes adjustment of spatial orientation. It is therefore a primary goal of the following analyses to show that this search assumption yields a detailed account of performance. To attain this goal, we focus upon a strategy analysis in Experiment 1 to explain the basic pattern of results for positive as well as for negative responses. In Experiment 2, we will address individual pattern complexity as a main residual factor to be explained.

As was shown in preliminary analyses (Geissler, 1995; Geissler & Lachmann, 1996; Lachmann, 1996; see Lachmann, 2000 for an overview), ESS effects on RT are consistent with the assumption that the task, which is explicitly stated as a comparison demand, becomes replaced in actual processing by a procedure of search through activated representations of equivalence sets of patterns to which the patterns to be compared belong. In the condition of categorical same–different comparisons, there are two relevant cases. Namely, that two patterns presented evoke representations that correspond either to the same equivalence set, or to two different sets. Correspondingly, a simple decision rule that produces a result equivalent to that of a direct pattern comparison reads: If two elements of an activated set representation match with test patterns, the response same can be elicited. If matches are distributed between two different equivalence set representations, the correct response is different. As will be seen below, this basic procedural idea provides the space for several variants of implementation that need to be compared with one another and with possible alternative explanations.
2. Experiment 1

2.1. Method

2.1.1. Participants
 There were 30 student volunteers (18 female) from the University of Leipzig, aged between 18 and 30 years, who either were paid or received course credit for their participation.

2.1.2. Materials and design
 Patterns of five dots on an imaginary 3 x 3 grid were used, leaving no row or column empty (Garner & Clement, 1963). The total of 90 patterns falls into 17 disjunctive subsets consisting of pattern elements that are equivalent in the sense that they can be transformed into each other by reflection and/or multiples of 90° of rotation (R&R subsets, equivalence sets; see Garner & Clement, 1963). These sets differ in size, depending on the symmetries of their pattern elements. Two patterns are invariant against the transformations, and therefore represent a set by themselves with set size 1. Eight subsets consist of four elements that can be transformed into each other. Furthermore, there are seven subsets of eight equivalent pattern elements. One example for each of the 17 subsets is shown in Fig. 1.

By combining the 90 patterns, four series of 271 pairs each were arranged. These pairs differed in matching components and structure of the involved stimuli (ESS). The patterns of 136 pair trials came from the same subset and had therefore, following the instruction, to be judged as same. Within these same cases, pairs consisting of physically identical patterns (identity matches, IM) and pairs of patterns identical by transformation (categorical matches, CM, that is matches excluding IM) are to be distinguished. There were 135 pairs that came from disjunctive subsets of either the same, or different set sizes. These pairs had to be judged as different (non-matches, NM).

Taking into consideration both the ESS of the patterns (1, 4, and 8) and the types of matching (IM, CM, and NM) amounts to a total of eleven types of combinations, five of which required a same and six a different response (for details see Fig. 2). Patterns with ESS = 1 under NM condition were not presented to protect participants against confusion (“illegal” 45° rotations provoking wrong same responses). Consequently, our analyses rely on 10 types of combinations (Fig. 2). As dependent variables, RTs and error rates were employed.

2.1.3. Apparatus
 Stimuli were presented using a display of red LEDs. Non-active LEDs were invisible. The display was controlled by a PC through a parallel port. The experiment was performed in a windowless room with indirect lighting approximating daylight conditions. The points of the patterns presented were 5 mm in diameter. The distance between two points within the 3 x 3 matrix was 13 mm. Consequently, the total expanse of the matrix was 41 x 41 mm and the visual angle subtended about 3.5°. The display was fixed at individual eye level, but there was no fixation of the subject’s
Responses were given through a separate unit by pressing one of two buttons representing, according to a counterbalanced design, either same or different judgments.

### Procedure
Participants were given a sheet of paper introducing them to the categorical instruction and the transformation rules as well as to the whole procedure of the experiment. Instructions urged them to react as fast, but also as accurately, as possible. Every subject took part in four sessions of about 30 min each. Before Session 1, participants had to perform 60 trials with an accuracy feedback and 30 trials without feedback to get used to the task. Before any further session, 10 warm-up trials had to be performed.

Patterns were presented successively. The first appeared on the left side of the display for 250 ms. After an inter-stimulus-interval (ISI) of 500 ms, the second pattern appeared on the right side of the display, remaining on until the response was given. There was no need for moving the head. After an inter-trial-interval (ITI) of 2500 ms the next trial started automatically.

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<table>
<thead>
<tr>
<th>identity matches</th>
<th>categorical matches (without physical identity)</th>
</tr>
</thead>
<tbody>
<tr>
<td>set size one i11</td>
<td>set size four i44</td>
</tr>
<tr>
<td>![Sample Image]</td>
<td>![Sample Image]</td>
</tr>
<tr>
<td>number of sets (ns)*elements(e)*factor (f)</td>
<td>ns*element combination(ec)*f</td>
</tr>
<tr>
<td>2<em>1</em>8=16</td>
<td>8<em>4</em>1=32</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>non matches</th>
</tr>
</thead>
<tbody>
<tr>
<td>set size four n44</td>
</tr>
<tr>
<td>![Sample Image]</td>
</tr>
<tr>
<td>ns<em>ec</em>(ns-1)*f</td>
</tr>
<tr>
<td>8<em>16</em>7*1/32=28</td>
</tr>
</tbody>
</table>

Total number of combinations: **271** (136 same & 135 different)
2.1.5. Results

For error rate analysis, responses of RTs between 140 ms and an individual outlier criterion \((\mu + 3\sigma | \text{RT} < 2000 \text{ ms})\) entered into computation. For RT analyses only correct responses within this time range were included. The overall mean RT was 504 ms (SD = 172 ms) and ranged from 415 to 610 ms for subjects, with the exception of one subject whose overall mean was 723 ms. The mean error rate was 8.2% and ranged from 5 to 12%, except for two subjects with 23% and 28% incorrect responses. Most subjects made <8% errors.

To check for effects of practice on RT and on error rate, analyses of variance were carried out. Generally, the Greenhouse–Geisser correction for significance was used. RT decreased significantly with the number of sessions, \(F(3, 29) = 41.5, p < 0.01\), following an exponential function (RT = 483.8 + 255e\(^{-0.64s}\) ms, with \(s\) denoting number of session; the factor session did not interact with any of the experimental factors). Error rate, \(F(3, 29) = 2.9, p > 0.05\), decreased significantly only between Session 1 and 2, \(F(1, 29) = 11, p < 0.01\).

Table 1 presents mean RTs, standard deviations and error rates for the 10 types of combinations as introduced above, reflecting both task and stimulus components. As expected, the results reflect very clear effects of ESS (1, 4, and 8) and type of matching (matches, that is IM & CM, non-matches). To check on main effects and interactions for RTs and error rates, analyses of variance were run.

Same responses with 472 ms on average required significantly less time than different responses with 538 ms on average, \(F(1, 29) = 81.3, p < 0.01\). This reflects the so-called “fast-same-effect” often observed in same–different experiments (Nickerson, 1969; see Farell, 1985, and Sternberg, 1998, for an overview; see also Section 2.3). The difference in error rate between same (7.1%) and different (9.3%) responses proved to be insignificant, \(F(1, 29) = 2.4, p > 0.1\). For same responses subjects needed significantly less time, \(F(1, 29) = 344, p < 0.01\, and made significantly fewer

Table 1
RT, standard deviation and error rate resulting from Experiment 1, further explanation in the text

<table>
<thead>
<tr>
<th></th>
<th>RT (ms)</th>
<th>Standard deviation (ms)</th>
<th>Error rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Same</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IM</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ESS 1</td>
<td>370.5</td>
<td>118.7</td>
<td>1.6</td>
</tr>
<tr>
<td>ESS 4</td>
<td>412.2</td>
<td>137.4</td>
<td>2.4</td>
</tr>
<tr>
<td>ESS 8</td>
<td>463.3</td>
<td>153.4</td>
<td>4.0</td>
</tr>
<tr>
<td>CM</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ESS 4</td>
<td>505.4</td>
<td>146.4</td>
<td>8.9</td>
</tr>
<tr>
<td>ESS 8</td>
<td>593</td>
<td>193.1</td>
<td>17</td>
</tr>
<tr>
<td>Different</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NM</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ESS 4</td>
<td>526.5</td>
<td>154.8</td>
<td>5.7</td>
</tr>
<tr>
<td>ESS 8</td>
<td>590.3</td>
<td>214</td>
<td>22</td>
</tr>
<tr>
<td>ESS 1 and 4</td>
<td>495.5</td>
<td>132.9</td>
<td>3.1</td>
</tr>
<tr>
<td>ESS 1 and 8</td>
<td>508.1</td>
<td>136.5</td>
<td>4.3</td>
</tr>
<tr>
<td>ESS 4 and 8</td>
<td>547.3</td>
<td>170</td>
<td>9</td>
</tr>
</tbody>
</table>
errors, $F(1, 29) = 68, p < 0.01$, for identity matches (435 ms/3.1%) than for categorical matches (546 ms/12.6%), disregarding set size 1, for comparability.

RT and error rate of same responses increased as ESS increased, $F(2, 58) = 328, p < 0.01$; $F(2, 58) = 82, p < 0.01$. This was also confirmed by separate analyses of RT, $F(2, 58) = 140, p < 0.01$ and error rate $F(2, 58) = 12.6, p < 0.01$ of IM, and RT, $F(1, 29) = 124, p < 0.01$, and error rate, $F(1, 29) = 38.7, p < 0.01$, of CM cases. To assess the simultaneous effects of the ESSs of both compared patterns for different responses, the sum $ESS' = ESS1 + ESS2$ of ESS values of compared patterns was used as a factor level. This yielded highly significant effects on RT, $F(4, 116) = 83, p < 0.01$, as well as on error rate, $F(4, 116) = 68, p < 0.01$.

A two-way analysis of variance of RTs for the same responses was carried out with the factors ESS and type of matching (using a $2 \times 2$ procedure since there is no ESS1 for CM). Significance was obtained for the main effects of ESS, $F(1, 29) = 160, p < 0.01$ and the type of matching, $F(1, 29) = 317, p < 0.01$, as well as for the interaction of these factors, $F(1, 29) = 27.6, p < 0.01$, which implies that the effect of ESS is bigger for CM.

2.2. Discussion

2.2.1. Model analyses

The results confirm the relevance of ESS as a basic parameter of processing for the paradigm under investigation. Specifically, the overall pattern of results agrees closely with that of Schmidt and Ackermann (1990): Mean RTs strongly depend on the ESSs of the patterns to be compared, even in the case of physical identity. The near linearity of the function (see Fig. 3) for positive responses supports our assertion of a serial check through evoked group codes representing the sets of transformationally related patterns to which given pairs of same items belong.

![Fig. 3. RT (ms) of identity matches and categorical matches as a function of ESS.](image-url)
Clearly, any model that is solely based upon comparison of isolated representations of stimuli will have difficulties with these findings. There is, however, at least one sophisticated version of this type of model which needs to be considered seriously. In this dependence on ESS is attributed not to the comparison process itself, but to stimulus encoding (see discussion in Pomerantz, 1977). This point will be one of the subjects of a separate section, Section 2.3.

To explore the exact nature of the assumed search process and to check upon the usefulness of the MGI rationale under the investigated conditions of short-term memory performance, several variants of search models were taken into consideration and corresponding regression analyses were performed. In the following model descriptions, a model representing a certain compromise between direct comparison and memory search will be indexed by the letter A, variants of strict MGI modeling by the letters B and C.

2.2.2. Model A

In this model, it is assumed that only the first of the two patterns of a pair of test stimuli evokes a representation of the pertaining equivalence set representation which persists up until the end of the ISI. The second stimulus is supposed to be compared one by one with the elements of the set representation evoked by the first stimulus. As processing is initiated immediately, there is no separate representation of the equivalence set pertaining to the second stimulus to be assumed. Let $N$ be the ESS of the first stimulus, and assume the search to proceed in random order. For a correct decision it would be sufficient to locate the second stimulus within the set evoked by the first pattern, which requires on average $\frac{(N+1)}{2}$ comparison steps for positive decisions. However, this would be at variance with the finding of a smaller slope between $\text{ESS} = 4$ and $\text{ESS} = 8$ for identity matches ($\text{IM} = 51 \text{ ms}$) as compared to categorical matches ($\text{CM} = 88 \text{ ms}$) and the significant interaction between $\text{ESS}$ (4 and 8) and the type of matching (IM and CM). This failure can, in a certain assimilation of the model to the principle of MGI, be corrected by the assumption that the relation of the evoked set to the first stimulus is always explicated by a mark indicating its position in the group code, which serves as termination criterion in case of physical identity of first and second stimulus (IM). The remaining matches do not correspond to relations explicates beforehand and thus provide no basis for termination. In other words, search in these cases should be exhaustive. This implementation of the model yields $N$ steps of checking for CMs, an average $\frac{(N+1)}{2}$ steps for IMs and $N$ steps for non-matches. Note that this version predicts a 1:2 ratio of slopes between IM and CM, as it was found in the present study and the study of Schmidt and Ackermann (1990).

2.2.3. Model B

Model A can easily be transformed into a completely representation-based version in the vein of MGI. To accomplish this, we have to introduce the corresponding equivalence set $S_2$ for the second stimulus in addition to the equivalence set $S_1$ evoked by the first stimulus. The search procedure is now to be conceived of as a serial search which proceeds in parallel or sequential order in the equivalence sets of $S_1$
and $S_2$. For positive decisions, these equivalence sets are identical. A self-terminating search for IM with $(N + 1)/2$ steps on average, and an exhaustive search for CM with $N$ steps can be motivated as above. For negative decisions, there are three sub-cases to be considered. If the search proceeds serially in parallel in each of the sets, processing can terminate after an exhaustive search through the smallest set, the largest set, or randomly after the first or second condition. This amounts to $N_{\text{min}}$, $N_{\text{max}}$, or $(N_{\text{min}} + N_{\text{max}})/2 = (N_1 + N_2)/2$ steps, in either case. If the search in both sets is assumed to proceed exhaustively in a sequence, the number of steps should be $N_1 + N_2$. These versions of the model will be referred to by B1–B4 in the following.

2.2.4. Model C

In model B, the asymmetry of processing between $S_1$ and $S_2$ is explained by a special termination condition for full identity. From the viewpoint of MGI, it would appear more plausible if this asymmetry derived from sequential constraints on processing rather than from a genuine representational difference. This can be embodied by assuming that $S_1$ and $S_2$ are always processed one after another, such that the check of the second stimulus always begins with the element of the equivalence set checked last. With this assumption, the search is supposed to be self-terminating for both $S_1$ and $S_2$. The responses become elicited after an additional process (see Section 2.2.5), which ascertains whether matches were found within the same equivalence set or in different sets. For this model $(N + 1)/2$ search steps for IM, and $(N + 1)/2 + (N + 1)/2 = N + 1$ search steps for CM are obtained. For NM, the model predicts $(N_1 + 1)/2 + (N_2 + 1)/2 = (N_1 + N_2)/2 + 1$ search steps.

2.2.5. Model decision

Provisional analyses have shown that real performance often deviates considerably from the predictions of even the best fitting of these models. As a major source of deviation, a shift of IM responses relative to CM and NM responses can be identified, suggesting an origin not in the search procedure, but rather in a stage of final decision required in CM as well as in NM. Therefore, a free constant $c$ was included in the analysis for each of the above models A–C.

Regression analyses were performed for the mean RTs of every condition and for those of same and different responses separately. Results are presented in Table 2. For evaluation from the point of view of MGI, it is important to consider, besides statistical indices, approximate invariance of estimated slopes (operation times) as a content-related criterion of validity (cf. Geissler & Puffe, 1983). This is motivated by the notion that there should be no principal difference between operations in the scanning of memory representations in positive and negative responses. Application of this criterion eliminates the models A, B2, and B4 for which the ratios of slopes are between 1.5 and 2. From the remaining variants B1, B3, and C, we favor model C not only because of its overall fit, but also because this model does not require any additional assumption to explain the difference in performance between conditions IM and CM.
Table 2
Results of regression analyses performed for mean RTs (DF = 9) and for those of “same” and “different” responses (DF = 4) separately using the predictors of the models A–C with (right) and without the free constant \( c \) (shift parameter)

<table>
<thead>
<tr>
<th>Model</th>
<th>( R^2_{adj} ) same/diff./total</th>
<th>Slope, same/diff./total</th>
<th>Intercept, same/diff./total</th>
<th>Free constant</th>
<th>( R^2_{adj} ) same/diff./total</th>
<th>Slope, same/diff./total</th>
<th>Intercept, same/diff./total</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.91/0.81/0.63</td>
<td>31.8/10.7/21.7</td>
<td>342/485/406</td>
<td>6.3</td>
<td>0.99/0.81/0.93</td>
<td>23.9/10.7/14.3</td>
<td>352/417/377</td>
</tr>
<tr>
<td>B1</td>
<td>0.92/0.92/0.48</td>
<td>31.8/12.6/20.1</td>
<td>341/488/424</td>
<td>6.8</td>
<td>0.93/0.92/0.94</td>
<td>14.3/12.6/14.6</td>
<td>372/402/376</td>
</tr>
<tr>
<td>B2</td>
<td>0.92/0.08/0.72</td>
<td>31.8/9.5/23.6</td>
<td>341/473/378</td>
<td>4</td>
<td>0.98/0.08/0.84</td>
<td>19/9.5/16</td>
<td>360/435/373</td>
</tr>
<tr>
<td>B3</td>
<td>0.92/0.87/0.80</td>
<td>31.8/16.4/27.6</td>
<td>341/450/375</td>
<td>3.6</td>
<td>0.99/0.87/0.97</td>
<td>20.2/16.4/19.5</td>
<td>358/391/363</td>
</tr>
<tr>
<td>B4</td>
<td>0.94/0.90/0.90</td>
<td>14.1/8.6/13.0</td>
<td>378/447/394</td>
<td>0</td>
<td>0.94/0.90/0.90</td>
<td>14.1/8.6/13</td>
<td>378/445/394</td>
</tr>
<tr>
<td>C</td>
<td>0.92/0.90/0.80</td>
<td>32/17.1/28.1</td>
<td>309/430/346</td>
<td>3.5</td>
<td>0.99/0.90/0.98</td>
<td>20.5/17.1/20</td>
<td>337/371/342</td>
</tr>
</tbody>
</table>

Note: The right side of the table shows the results of the regression including the free constant \( c \) (shift parameter). As Beta the adjusted \( R^2 \) \( R^2_{adj} \) for low DF was used. \( R^2_{adj} = R^2 - ([1 - R^2)a]/(b - a^*) \), with \( a = \) number of independent variables; \( b = \) sum of caseweights; \( a^* = \) number of coefficients (including intercept).
A further argument in favor of model C is the following formal one. For B₁–B₄, an additional contribution to variance is expected to occur for IM, since, if the search is random, the number of test operations in self-terminating as opposed to exhaustive search should vary as a function of the start position. However, no evidence in support of this prediction was found. To appraise the variances per operation, the formula \( \text{VAR}(\text{op}) = \text{VAR}/(\text{ESS} + 1/2) \) for IM and \( \text{VAR}(\text{op}) = \text{VAR}/\text{ESS} \) for CM was used. For pattern pairs of set size 4, variance per operation is somewhat higher for IM than for CM, but not significantly so, \( F(1, 29) = 2.9, p = 0.099 \). No difference at all resulted for patterns of set size 8, \( F(1, 29) = 0.76, p > 0.1 \). The data fit for model C is shown in Fig. 4.

2.3. Discussion of alternatives

The experimental conditions in the present study are hardly comparable with those of typical same–different experiments (Egeth, 1966; Gibson, 1969; Nickerson, 1969; see Farell, 1985; Lachmann, 2000, or Sternberg, 1998 for general overview) using either features, or a dimensional structure for variation. Furthermore, they cannot be compared with the same–different experiments performed to investigate levels of processing (Bartram, 1976; Klatzky, 1972; Posner & Mitchell, 1967) where the term categorical was used for a higher level of abstractness to define a same category (Posner et al., 1969).

If we try to define the conditions of the present study in terms of a dimensional structure, considering pattern structure (form) and orientation as dimensions under disjunctive instruction (Farell, 1985; see also Miller, 1978), RTs in NM would be expected to be longer than in CM, which is not the case (see Fig. 3). The short RTs for IM are typically found in same–different experiments under conjunctive instruction (Farell, 1985) and are referred to as “fast-same-effect”. However, theories trying to explain this effect (Bamber, 1969; Eriksen, O’Hara, & Eriksen, 1982; Farell, 1985; Krueger, 1978; Proctor, 1981, 1986; Posner, 1978) do not account for the strong ESS effect within all conditions of our experiment, and especially not for the fact that
this effect is also observed in IM, which generally is also an argument against mental transformations occurring within CM conditions (Posner, 1978).

The general relations between IM, CM, and NM obtained in the present study could be correctly described by modifying the confluence model of Eviatar, Zaidel, and Wickens (1994). For the given task we can assume two parallel processes, one for detecting physical identity and one for detecting categorical identity, which leads to a confluence of agreeing arguments in IM, and contradicting arguments in CM. However, this still provides no explanation for the ESS effect and its interaction with the types of matching (IM vs. CM). In fact, there seems to be no model of same–different comparisons, or of more general processing models, that would allow for a quantitative description of the observed ESS effects comparable to that of the search models introduced above.

Since ESS was suggested to be a direct measure for goodness (Garner, 1962), it was used by several investigators to answer the question of whether or not goodness influences the speed of encoding (Bell & Handel, 1976; Clement & Vernadoe, 1967; Checkosky & Whitlock, 1973; Garner & Sutliff, 1974; Hock, 1973; Pomerantz, 1977). It is not the aim of the present study to discuss this issue, which is not definitively answered in the literature (Biederman et al., 1994). However, encoding speed should not be ignored as a viewpoint for possible explanations of ESS effects.

In the context of theories that explain the “fast-same-effect” as a result of an encoding facilitation (Entus & Bindra, 1970; Krueger, 1978; Proctor, 1981), it could be argued that the smaller ESS effect in IM in comparison to CM is a result of the fact that a stimulus structure already encoded will be more advanced for the second encoding (see Farell, 1985; Nickerson, 1975; Pachella & Miller, 1976, for results indicating that encoding facilitation is not tenable as a sufficient account for the effect). Although at first sight, model C might appear as an implementation of this idea, closer consideration shows the contrary. In fact, SOAs of 750 ms, as employed in the experiment, exceed the overall mean RT, and are much longer than the time required for encoding the first stimulus of any presented pair of stimuli. An encoding explanation has therefore to attribute effects of ESS solely to the second stimulus of any pair. If this is true, however, it still remains a mystery why ESS dependence, in the case of IM, settles at about half of the effect observed in CM instead of leveling out completely.

Furthermore, the results for negative decisions argue against a simple encoding hypothesis for ESS effects (see Table 1). For pairs of patterns differing in ESS values, RTs are expected to be shorter when the second stimulus belongs to the set of smaller ESS, since only encoding of the second stimulus should matter. In contrast to this expectation, for combination of the ESSs of 4 and 8, even an opposite effect was found, $F(1, 29) = 51, p < 0.01$. ESSs of 1 and 4 yielded an insignificant effect of a few milliseconds in the predicted direction, $F(1, 29) = 6.5, p > 0.05$. No effect was obtained for the ESS combinations 1 and 8, $F(1, 29) = 1.3, p > 0.05$. To conclude, available evidence rules out any simple hypothesis of the influence of ESS upon RT which is solely based upon encoding of the second stimulus. Correspondingly, the assumption that the first stimulus facilitates encoding of the second stimulus
by making a new encoding operation superfluous, is of no value for explaining faster processing of pairs of fully identical patterns as compared to different, categorically identical patterns. Instead, the above model analysis demonstrates convincingly that ESSs of both patterns of a pair contribute in a definite way to the total processing load. The origin of the effects after encoding the second stimulus, and their order of magnitude strongly suggest that the underlying neural processes are of a central nature. This is a characteristic that fits in with the MGI claim that processing operations correspond to steps of top-down matching of task-related representations to maintained sensory evidence.

ESS effects in IM were quoted above as evidence against explanations based upon mental rotation or reflection operations (Cooper & Shepard, 1975; Shepard & Metzler, 1971). The present study is not a typical mental rotation task in Shepard and Metzler’s sense (closer would be Corballis & Roldan, 1974; Corballis, Zbrodoff, Shetzer, & Butler, 1978; Pashler, 1990; see also Jolicoeur, 1985). Nevertheless, for central processes involved in comparison of patterns in pairs, which in the case of positive decisions represent rotated or mirrored versions of each other, it still appears implausible that no processes of mental rotation/reflection type should be involved (for discussion see Corballis & Roldan, 1974; Egeth & Blecker, 1971; Pashler, 1990). One could therefore argue that the pattern of effects is the result of a combination of transformation and encoding operations. Supposing seriality for these components, the time to transform the representations into each other in CM and NM would add to encoding time (but see Ruthruff, Miller, & Lachmann, 1995; Ruthruff & Miller, 1995; for a more general discussion see for example, Besner, 1978; Dell’Acqua & Jolicoeur, 2000; Miller, 1982; Pashler, 1984; Van Selst & Jolicoeur, 1994). In IM, as no transformation is required, observed ESS effects would then represent merely encoding. However, these and similar attempts to explain the effects must fail for qualitative reasons. Mental rotations imply contributions to RT which are proportional to gradual differences in pattern orientation. Roughly, on average, these differences do not change for CM from ESS = 4 to ESS = 8, and thus cannot explain the additional RT increase in comparison to IM pairs. This argument readily expands to negative decisions with the finding that mean RTs, in this case for pairs of patterns of identical ESSs 4 or 8, are practically equal to those of corresponding ESSs for positive decisions in the CM condition (see Table 1). This is, however, exactly what the search model predicts.

These conclusions, which are based upon average ESS dependencies, can be strengthened by the evaluation of selected sets of pairs of test stimuli. For example, for ESS = 4 in CM results in an insignificant RT difference of 3 ms, $F(1, 29) = 0.35$, $p = 0.56$, between pairs with 90° or 180° rotation among pattern members disregarding direction of rotation. No significant difference is obtained if either direction is taken into account.

2.4. Effects of individual pattern goodness

The models considered so far disregard effects of individual pattern structure arising within sets of patterns of identical ESSs which, according to MGI, should
constitute another component of processing. Checkosky and Whitlock (1973) noticed effects of individual pattern regularities without paying special attention to them.

In comparison tasks, demonstration of dependencies of individual pattern properties is straightforward only for matching pairs, that is in IM and CM. In this case both of the compared patterns are of identical structure (same subset) and thus, effects of individual pattern properties can easily be separated from ESS effects. For these conditions, Schmidt and Ackermann (1990) found RT differences between patterns of identical ESSs which are produced by different transformations (see also Lachmann, 1996). Fig. 5 provides an illustration of the extent to which RTs between patterns belonging to groups of identical ESSs in Experiment 1 differ.

Intuitively, looking at the extreme cases, shown as samples in Fig. 5, one can realize that RT within those ESS groups co-varies with goodness of pattern members. Correlational analyses, using the goodness ratings published by Garner and Clement (1963) and the corresponding RT means of Experiment 1, substantiate this impression. The correlations are in all cases positive, although only for physical matches and patterns of ESS = 4 significance is obtained, \( R(IM, ESS = 4) = 0.74, \ p = 0.036; \ R(IM, ESS = 8) = 0.47, \ p > 0.1; \ R(CM, ESS = 4) = 0.47, \ p > 0.1; \ R(CM, ESS = 8) = 0.51, \ p > 0.1. \)

In the present context, it is of considerable interest to explore whether or not the effects of ESS and those of structural pattern specificity correspond to distinguishable stages of processing. From the point of view of MGI, the structure of single patterns is supposed to represent a separable constituent of pattern codes. Therefore, it appears likely that this part of the representation codes will be processed only once during the entire recognition process. In a stage terminology this gives preference to a separate-stage additivity hypothesis.
A difficulty in checking upon this hypothesis arises from the fact that the current theory does not provide a rule for a priori computation of pattern complexities that would unambiguously apply to the specific patterns employed in Experiment 1, and thus deliver predictions of the additional processing load contributed by the individual pattern structures. An attempt to invent such a rule ad-hoc for the employed patterns was not successful in due time. As a consequence, in Experiment 2, we took an experimental approach by letting participants of Experiment 1 judge individual pattern goodness. In analogy to the calculation above in which Garner’s rating data were employed, we suppose that transformational properties of patterns represented by ESS and idiosyncratic characteristics are processed independently.

3. Experiment 2

3.1. Method

3.1.1. Participants
There were 19 participants (10 female), who all took part in Experiment 1.

3.1.2. Materials and design
To obtain estimates of subjective complexities for the 17 pattern sets described in Experiment 1, we used prototypes by taking one pattern from each of the sets of structurally different patterns as suggested by Garner and Clement (1963). Thus, seven patterns of $\text{ESS} = 8$, eight patterns of $\text{ESS} = 4$, and the two patterns that represent by themselves sets of $\text{ESS} = 1$, were employed. As a dependent variable the ratings given on a nine-point scale were used. No latencies were measured.

3.1.3. Apparatus and procedure
The patterns were presented on a computer screen. The size of the imaginary matrix for producing the dot patterns was $73 \times 73$ mm. The distance between two neighboring dots on the matrix was 17 mm. The dots had a diameter of 13 mm and were presented in red on a black background. The 17 patterns were shown in random order, with the restriction to present patterns from sets with the same ESS no more than three times in a row. This kind of presentation was carried out six times, one immediately after the other. Thus every pattern had to be judged six times with a distance of 16 trials on average (and with the restriction of a minimum distance of three trials before the same pattern had to be rated again). A total of 102 judgments was required, resulting in 17 rating means and pertaining standard deviations. Since the subjects had already attended one session of the RT experiment, they were familiar with the material. In spite of that they received a piece of paper on which the 17 patterns were printed in random order. In the instructions given on the screen, participants were asked to decide which of the respective patterns appeared more complex or more simple in relation to the other patterns. It was emphasized that only the subjective impression is relevant, and that there is no need of response consistency in rating the same pattern. To give the response,
participants had to press one of the number buttons on the computer keyboard that represented the ratings from very complex = 9 to very simple = 1. To minimize order effects after giving the judgment, the respective pattern was masked for as 4 s by a full 3 × 3 matrix. Thereafter the next pattern to be rated was shown at a different location on the screen.

3.2. Results and discussion

3.2.1. Ratings

A total of 1938 ratings was recorded. The overall mean of the ratings was 4.52 with individual means ranging from 3.3 to 5.6, testifying proper use of the scale. The mean was found to decrease with the number of repetitions, but after Greenhouse–Geisser correction, the effect just slightly failed to be significant, \( F(5, 90) = 2.6, p = 0.055 \) (\( p = 0.042 \) with Huynh–Feldt). A decrease of variance with repetition was not significant either, \( F(5, 90) = 2.3, p > 0.05 \).

The ESS affected the ratings significantly, \( F(2, 36) = 490.1, p < 0.01 \). While patterns from sets of ESS = 8 were rated 6.8 on average, patterns of ESS = 4 sets were rated 3.3, and the two singular patterns were judged as very simple, by 1.3 on average. As expected, this confirms findings of Garner and Clement (1963), \( R = 0.96, p < 0.01 \), whose participants had to rate the 17 patterns only once on a seven-point scale. As shown in Table 3, for our data as well as for those of Garner and Clement, there is a considerable pattern-specific variance of ratings for patterns of one and the same ESS, which even shows an overlap between ESS = 4 and ESS = 8 in both data sets.

3.2.2. Relation to RT in Experiment 1

As previously explained, for the pattern-specific analyses, only the RTs for pairs of patterns from the same subset were used, which led to 17 pattern-specific means for IM and 15 means for CM (no ESS = 1), respectively.

Significant correlations were found between mean ratings and pattern-specific RT means for IM, \( R = 0.95, R_{adj}^2 \) (adjusted \( R^2 \), see note Table 2 = 0.90, \( p < 0.01 \) and CM, \( R = 0.90, R_{adj}^2 = 0.80, p < 0.01 \), as well as for overall means of same responses, \( R = 0.92, R_{adj}^2 = 0.83, p < 0.01 \).

To investigate about the origin of this effect, multiple regression analyses were performed for the overall means, and for the four subsequent sessions of Experiment 1 combining model C with ESS-trend-reduced mean ratings. The trend reduction guaranteed the independence of the second factor from ESS. The shift parameter (constant c) was calculated for each session separately. The results shown in Table 4 document a small but significant influence of individual pattern complexity, which reduces slightly with practice in the task.

This can be interpreted as moderate evidence for a decrease of the pattern-specific processing load with practice. A comparison between data and predictions for the mean of all sessions is provided by Fig. 6.

From the viewpoint of MGI it would be important to know whether or not processing of this component differs between IM and CM conditions. To answer this
Table 3
Pattern set-specific mean ratings of Experiment 2 (LACH), ratings taken from Garner and Clement, 1963 (GAR) transformed in a nine-point scale equivalent for compatibility, and mean RTs (ms) resulting from Experiment 1 for identity matches (IM) and categorical matches (CM)

<table>
<thead>
<tr>
<th>Prototype</th>
<th>Mean rating</th>
<th>Mean RT (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LACH</td>
<td>GAR</td>
</tr>
<tr>
<td>ESS4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1)</td>
<td>1.47</td>
<td>2.29</td>
</tr>
<tr>
<td>(2)</td>
<td>5.81</td>
<td>4.50</td>
</tr>
<tr>
<td>(3)</td>
<td>3.66</td>
<td>3.92</td>
</tr>
<tr>
<td>(4)</td>
<td>3.52</td>
<td>2.88</td>
</tr>
<tr>
<td>(5)</td>
<td>3.98</td>
<td>2.88</td>
</tr>
<tr>
<td>(6)</td>
<td>1.64</td>
<td>2.20</td>
</tr>
<tr>
<td>(7)</td>
<td>3.00</td>
<td>1.99</td>
</tr>
<tr>
<td>(8)</td>
<td>3.54</td>
<td>2.24</td>
</tr>
<tr>
<td>ESS8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1)</td>
<td>7.22</td>
<td>6.57</td>
</tr>
<tr>
<td>(2)</td>
<td>4.71</td>
<td>4.37</td>
</tr>
<tr>
<td>(3)</td>
<td>6.72</td>
<td>6.17</td>
</tr>
<tr>
<td>(4)</td>
<td>6.37</td>
<td>6.13</td>
</tr>
<tr>
<td>(5)</td>
<td>7.33</td>
<td>5.90</td>
</tr>
<tr>
<td>(6)</td>
<td>7.07</td>
<td>6.67</td>
</tr>
<tr>
<td>(7)</td>
<td>8.14</td>
<td>7.06</td>
</tr>
<tr>
<td>ESS1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1)</td>
<td>1.25</td>
<td>1.32</td>
</tr>
<tr>
<td>(2)</td>
<td>1.40</td>
<td>1.29</td>
</tr>
</tbody>
</table>

Table 4
Results of a multiple regression analyses performed for the RT of each session and the total data set using model C and ESS-trend reduced mean ratings as factors

<table>
<thead>
<tr>
<th>Session</th>
<th>Constant (c)</th>
<th>(R^2_{adj}) model C</th>
<th>(R^2_{adj}) model C + Ratings</th>
<th>Beta-weight model C</th>
<th>Beta-weight ratings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Session one</td>
<td>2.1</td>
<td>0.85</td>
<td>0.90</td>
<td>0.92</td>
<td>0.25 ((p &lt; 0.01))</td>
</tr>
<tr>
<td>Session two</td>
<td>2</td>
<td>0.92</td>
<td>0.95</td>
<td>0.96</td>
<td>0.16 ((p &lt; 0.01))</td>
</tr>
<tr>
<td>Session three</td>
<td>2.7</td>
<td>0.91</td>
<td>0.92</td>
<td>0.95</td>
<td>0.12 ((p &lt; 0.01))</td>
</tr>
<tr>
<td>Session four</td>
<td>3.9</td>
<td>0.93</td>
<td>0.95</td>
<td>0.97</td>
<td>0.12 ((p &lt; 0.05))</td>
</tr>
<tr>
<td>Total</td>
<td>2.7</td>
<td>0.93</td>
<td>0.96</td>
<td>0.97</td>
<td>0.12 ((p &lt; 0.05))</td>
</tr>
</tbody>
</table>

Note: \(R^2_{adj}\) = adjusted \(R^2\) (see Table 2); \(c\) = shift parameter; Ratings = ESS--trend reduced mean ratings.
question, regression was repeated with the modification that the weight of the ratings was doubled for CM trials. This would be adequate if the corresponding information would be processed together with the orientation information. However, the data do not enable a decision on this issue. Since the portion of variance that individual pattern structure accounts for is small as compared to that of the search process represented by model C, there is practically no change of fit in comparison to the above equal-weight model.

4. General discussion

The results of this study give strong support to the assumption that in actual performance, at least under the conditions investigated here, a task stated as a comparison between two objects can become replaced by a search through evoked sets in memory which equivalently solves the task. This search can be modeled as a serial scan in an approximation which is no worse than that obtained for the classical search paradigm of item recognition (Sternberg, 1966). For the conditions under study, we can therefore claim that the memory-guidance approach MGI, which originally was developed for tasks dominantly relating to object representations in long-term memory, applies to short-term representations constructed in working memory as well. The results of our analyses contradict a traditional encoding view of the observed effects. Furthermore, no evidence of mental rotation/reflection effects could be found, which would have been expected if the task were solved by direct matching of internal representations of patterns to be compared. This agrees with, and perhaps helps to more deeply understand findings on performance with natural objects and
artifacts that consistently demonstrated that effects of orientation cannot be explained on the basis of mental rotations (Dickerson & Humphreys, 1999; Lawson & Humphreys, 1996; see also Lachmann, 2002). Dickerson and Humphreys’ results point to the composition of multiple representations. In this way, they are comparable with our results.

Our results exclude explanations by mental rotation/reflection operations, not only because RTs depend on ESS even in cases of full identity of compared patterns, but also from a rotation/reflection account, it cannot be seen why comparisons of patterns belonging to larger equivalence sets should take any longer than those of patterns belonging to smaller sets. The constancy of estimated time consumption per operation implies that in the present task, differences in angular orientation on average do not matter at all. Even durations of some 20 ms per operation are, by order of magnitude, not compatible to those found for mental rotations/reflections which are regularly much longer.

What remains of the above analyses that put the observed phenomena into relation to effects well-known from other paradigms, is a strong analogy to encoding effects, an increase of processing time with stimulus complexity, and a decrease when identical stimuli are processed in close temporal neighborhood. The crucial difference is that the processes involved in the task under consideration refer, in a task-specific way, to codes of pairs of stimuli which can be constructed only after the second stimulus is presented. In contrast to encoding in a traditional sense, which is an early process, these processes must therefore be of a late, central character. Taking this into account, the analogy can be read as follows: Central, task-specific encoding in categorical same–different situation leads to two group codes in the case of CM and NM conditions and to only one in the IM condition. Consequently, two group codes have to be searched through in the former conditions and only one in the latter. This explains the procedural similarity under CM and NM and the specific difference between CM and IM.

Experiment 2 revealed that task-specific codes must be assumed to include information specifying individual structural pattern properties under all conditions (IM, CM, and NM). The data are compatible with the view that this part of internal pattern representation is related to an independent stage of processing whereby only processing of the second stimulus can be reflected in the data. Our data do not allow a specific statement, in relation to the search model outlined in this paper, on how individual pattern structure is processed. Also, at present, the question whether similar statements are possible for negative responses, will remain unanswered.

While the comparison-via-search phenomenon is novel and may open new vistas in the analysis of human cognition in other cases, it is still far from being completely understood. Although rotation/reflection explanations in a traditional sense are excluded, provisional analyses (Lachmann, 2000) show that RTs of CM differ in various ways systematically depending on the transformational distance of the patterns to be compared. Likewise, performance is generally not independent of the sequence of presentation of two patterns. Sensitivity to conditions of serial context would have to be expected if assuming in a sophisticated version of the model C that task-specific
encoding does not always start from the same prototypes, but that the role of the internal referent may flexibly change as a function of encoding operations. Since order effects of these types vary considerably among subjects, it is difficult to model them in detail. This issue is therefore to be left to future investigations which are planned to make the notion of group codes formally more explicit.

A limitation of the present investigation is that the results refer only to the task demand of categorical comparison. It is still unknown what happens in particular in the simpler situation where the participants are instructed to respond with same only when patterns are identical in structure and in orientation. From a pilot study (Lachmann, 2000; Lachmann & van Leeuwen, 2002; see also Berti, Geissler, Lachmann, & Mecklinger, 2000), we know that RTs of matching pairs in this task still depend upon ESSs of the component patterns. Thus, it would seem very likely that direct comparison is replaced by a search process in this task too. Latencies of negative decisions (including CM), however, do not depend on ESS. This could indicate that negative decisions are derived by exclusion of match, probably by a time criterion of waiting.

Generalization of MGI to working-memory-based performance implies many more questions that cannot be addressed here. In general, for a proper understanding of complex recognition under varying constraints of task demand and environmental stimulus conditions, it will be of particular importance to know how different types of regularities become integrated into representations guiding task-specific executive control.

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