Cognitive Modelling of a Mental Rotation Task Using a Generalized Spatial Framework

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Abstract

Bespoke cognitive models of mental spatial transformation, like those used in mental rotation tasks, can generate a very close fit to human data. However these models usually lack grounding to a common spatial theory. In turn, this makes it difficult to assess their validity and impedes research insights that go beyond task-specific limitations. We introduce a spatial module for the cognitive architecture ACT-R, serving as a framework offering unified mechanisms for mental spatial transformation to try and alleviate those problems. This module combines symbolic and spatial information processing for three-dimensional objects, while suggesting constraints on this processing to ensure high theoretical validity and cognitive plausibility. A mental rotation model was created to make use of this module, avoiding custom-made mechanisms in favor of a generalizable approach. Results of a mental rotation experiment are reproduced well by the model, including effects of rotation disparity and improvement over time on reaction times. Based on this, the spatial module might serve as a stepping stone towards unified, application-oriented research into mental spatial transformation.

Keywords: spatial cognition; mental spatial transformation; mental rotation; ACT-R

Introduction

The ability to imagine physical interaction with arbitrary objects in a physically existing space and to assess objects and their attributes based on this mental representation is a fundamental aspect of human life. Forming such a mental representation is possible through the interplay of multiple cognitive processes. These processes of mental spatial transformation are governed by common criteria that directly influence the complexity, perceived difficulty and feasibility of altering the representation (Harris, Hirsh-Pasek, & Newcombe, 2013).

Mental rotation research, as a subfield of research into those processes, has established itself as a mainstay paradigm of experimental psychology. Mental rotation refers to the mental examination of real or simulated objects so that statements about their attributes can be made beyond their initial presentation, most often their similarity to other objects. Processes of mental rotation are, on one hand, ubiquitous in everyday life: they contribute greatly to our understanding of environments by helping us assess objects and possible interactions with them. On the other hand, the phenomenon is usually studied with the use of stripped-down, abstract objects; facilitating testing in laboratory conditions but removing real-world meaning.

Performance in mental rotation tasks is heavily influenced by task difficulty and experience (Shepard & Feng, 1972). Individual traits like reference frame proclivity (Gramann, 2013), additional workload or time pressure additionally influence mental spatial transformation. An understanding of processes underlying mental rotation has great potential, especially for economic applications, like improved product ergonomics (e.g. improving ease of use and perceptibility of features), but also for accessibility (e.g. identifying [dis-]advantages of individual traits). Cognitive modeling bases its predictions of task performance on postulated process models, which are in turn embedded into the framework of a cognitive architecture. This architecture combines multiple theories of mental processing to a holistic system that allows researchers to make general and plausible statements on cognitive processes. In the cognitive architecture ACT-R (Anderson et al., 2004), this is achieved through so-called cognitive modules which represent abstract processing stages set between neurophysiological activity and psychological correlates. Therefore, the action and interaction of these modules correspond to mental processing of declarative information and procedural action knowledge. Process models are quantified and encoded into production rules, i.e. assumptions about mental processes, that are subsequently validated with experimental data and, if necessary, engineered towards a closer fit to these data. While cognitive models encode assumptions about mental processes for specific tasks, more general mental mechanisms are implemented in the form of aforementioned modules. Hence, to model mental spatial transformation validly, the architecture needs to support a plausible implementation of it. This would then allow cognitive models of similar modalities to make use of a common, unified processing framework. By mitigating the reliance on highly task-specific assumptions and tailor-made process models in favor of a general framework, models of spatial cognition could offer higher validity and broader generalizability of their predictions.

Prior Research

Shepard and Metzler (1971) introduced an experimental paradigm for mental rotation. Their work examined the influence of rotation between two same or mirrored objects on the time needed by participants to decide if the presented objects match. They found a linear relationship of rotation discrepancy on reaction times. A follow-up study on mental folding (Shepard & Feng, 1972) showed similar results. Here, a folding pattern was required to be assembled into a cube shape to decide if it was a copy of a reference cube that was also presented. A linear effect of task difficulty on reaction times was found. Interestingly, the experiment also showed what the researchers perceived to be an upper limit on mental spatial transformation ability –above a certain threshold of required folds, reaction times increased considerably and non-linearly. Consequently, this result could be a pointer towards a general limitation on the amount of transformations that can be applied on an internal spatial representation.

Just and Carpenter (1976) used eye tracking during a mental rotation study to determine the existence of distinct cognitive stages. Based on their results, they proposed three general stages of cognitive processing: initial search, transformation and comparison, and confirmation. These stages can serve as an approximation for spatial cognition in general: a visual encoding phase, a transformation phase and a comparison or matching phase.

Eye tracking was also used during a mental folding experiment to try and find correlates for cognitive stage switching (Preuss, Hilton, & Russwinkel, 2020). Differences in gaze position switches and gaze durations were found that correlated with task difficulty. This was interpreted as signifiers of stage switching and stage duration, respectively.

To further differentiate processes during mental rotation and investigate possible solving strategies, Yuille and Steiger (1982) presented a study on objects with different complexities. While showing that object complexity has a direct influence on solving time, they introduced their theory of two distinct solving strategies: if an object is "familiar" enough, it can be transformed holistically, meaning as a whole; if the object is not recalled, it must be transformed in a piecemeal fashion, meaning it is separated into several parts or features which are then processed in sequence. This distinction proved to be a popular explanation for learning effects in mental rotation and mental spatial transformations in general.

Harris et al. (2013) reviewed differences and similarities between mental rotation and mental folding as the most common paradigms in mental spatial transformation research. While the tasks differentiate in the specific way a stimulus is processed, Harris et al. identified several attributes that underlie both processes, for instance physical analogy, malleability and predictiveness of success in *Science, Technology, Engineering & Mathematics* (STEM) fields. This work points to spatial cognition as a technical, trainable skill. Similar results were obtained by Wright, Thompson, Ganis, Newcombe, and Kosslyn (2008), who also compared skill development in a mental rotation and a mental folding task, in addition to a verbal analogy task. Learning one spatial task improved proficiency in the other tasks, but not as pronounced for the non-spatial task. Notably, the researchers argue that improvement comes mostly from improved encoding and transformation preparation processes, less from transformations per se, implying learning to stem largely from non-spatial mechanisms.

A cognitive model for a mental rotation task was previously introduced by Peebles (2019a). Peebles implemented both piecemeal and wholesale strategies on a simplified visual representation. Different to the approach presented here, the model was mostly self-contained and relied on default ACT-R mechanisms, with only slight changes to the architecture.

Gunzelmann and Lyon (2007) first proposed the concept of a cognitive module dedicated to spatial transformations. They presented a relatively complex mechanism, making use of several smaller information processing units. Unfortunately this approach has not yet been implemented into a cognitive architecture.

Several other approaches for mental transformations not relying on internal, three-dimensional representations exist: arguments for reliance on mental imagery (Peebles, 2019b; Lovett & Forbus, 2013), purely physical reasoning (Forbus, 1984; De Kleer & Brown, 1984) or syllogistic representations (Barkowsky, Knauff, Ligozat, & Montello, 2007) have been made for mental spatial transformations. The cognitive architecture SOAR offers a mechanism (*Spatial and Visual System*, SVS) that combines symbolic and spatial information (Laird, 2008).

This paper presents a cognitive task model for a mental rotation task that incorporates such a spatial framework for ACT-R, proving the usefulness of an additional module dedicated to spatial processing. This module is proposed as an extension to the cognitive architecture, integrating seamlessly into its existing structures and allowing multiple modalities of mental spatial processing to be simulated in a unified manner. It serves as an interface for the mathematically correct computation of three-dimensional space while processing it in a cognitively plausible way, without having to rely on overly task-specific assumptions about spatial processing. The spatial module presented in this paper shows a similar concept to the one suggested by Gunzelmann and Lyon (2007), but foregoes many of their proposed mechanisms in favor of a seamless integration into ACT-R's existing architecture. Default ACT-R modules are used for memory retrieval and for comparison purposes. Additionally, by integrating the proposed module into existing methods for simulating module activity and, by extension, brain activity, model predictions can be compared by brain-imaging data of participants in the actual experiment (Prezenski & Russwinkel, 2016).

The module's validity is pending on further assessment of its ability to predict mental spatial transformation processes for several modalities beyond mental rotation. As multiple design decisions are as of now made intuitively, open questions on structure, function and cortical localization of the module are tended to by current and upcoming research.

Methods

Spatial Module

The mental rotation model uses a dedicated spatial module added to ACT-R's default architecture, facilitating the processing of mental spatial transformations. Based on work by Gunzelmann and Lyon (2007), the idea is to offer seamless functionality for three-dimensional data in ACT-R in a cognitively plausible fashion. In contrast to the aforementioned work, the framework presented herein avoids episodic and allocentric buffers and relies instead on standard ACT-R mechanisms.

The spatial module aims to offer better explainability, applicability and validity for cognitive models of spatial cognition by offering a common theoretical ground for frequently shown effects such as differences in spatial strategies or influence of higher task difficulties on task solving. A unified mechanism for simulating mental spatial transformations would offer modelers both the ability and the constraints necessary to do so with high reliability and high validity, respectively. Effectively this would create a general framework spanning multiple paradigms of mental spatial cognition research, such as mental rotation or mental folding. In consequence, to the best of our knowledge it would be the first cognitive modeling approach to explain both paradigms in a satisfactory manner.

Spatial objects are encoded in standard chunks, ACT-R's basic unit of information, extended by information representing the object in 3D space in the form of so-called point clouds. This additional information is predefined for each spatial object, either implicitly by the model's environment or the modeler themselves. Point clouds were chosen for their versatility, scalability and relative ease of computation. They are able to represent objects in arbitrary detail, allowing modelers to focus on features relevant to their model. Extending chunks in this manner allows for full compatibility with all default ACT-R mechanisms such as vision or memory modules, while at the same time allowing algebraic manipulation of objects defined in this manner, i.e. being translated, rotated and rescaled in three-dimensional space. Furthermore, spatial objects can be compared and angles between objects can be measured. In practice, this extends the symbolic capabilities of ACT-R with the ability to perceive and interact with geometric properties. Analogous to how visual information is processed in ACT-R, the transition between geometric and symbolic information of perceived features is handled by the models themselves, in contrast to e.g. SOAR's similar mechanism (Laird, 2008).

Cognitive operations on spatial objects are handled by two buffers: a storage buffer for maintaining mental spatial representations (the *spatial* buffer) and an action buffer for applying transformation intention to said representation (the *spatial action* buffer). Spatial chunks contain point clouds and optionally additional spatial information like separable parts, angles for internal transformation or other features. Transformations on the representation are requested through the action buffer and, if within limits set by architectural and modular constraints, applied to the spatial object. The core function of the module is calculating a time delay for operations conducted through it. It does this through a transformation cost function which draws from currently available information to calculate an appropriate time frame for a transformation process to take place. Currently the following simple formula is used:

$$Transformation\ delay = F * M * x$$

including a delay factor (F) which can be set as a parameter with a default value of 0.005s, an optional modality factor (M) to assign weights to different transformation modalities, such as mental rotation or mental folding (if required for model adjustments) and the raw input value of the transformation (x). This formula is an attempt to find a common denominator underlying mental spatial transformations. By combining symbolic processing with three-dimensional spatial information, several limitations by aforementioned prior research could be alleviated or overcome. Contrary to task-specific approaches, this framework constrains models to adhere to established mechanisms of cognitive spatial processing which facilitates explainability, validity and generalizability in model creation. Additionally, compared to methods relying on default mechanisms of ACT-R (e.g. using the imaginal module to store and process simplified spatial information as in Peebles, 2019a), the presented module enables symbolic calculations with true three-dimensional data. Finally, this module serves as a solid foundation for more complex models orientated away from lab conditions and towards real-world applications.

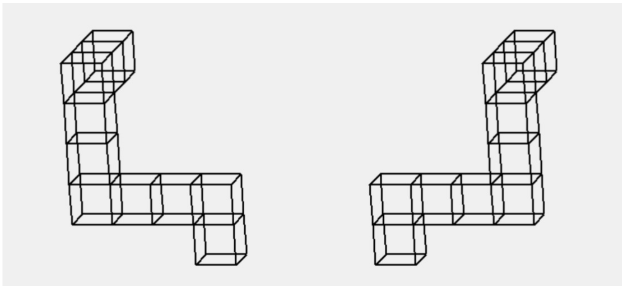

Figure 1: An example picture of 3D mental rotation stimuli as presented to the model. For simplicity, each cube is drawn around a single 3D coordinate. Multiple coordinates make up the point clouds of the whole figure and its features (i.e. straight sections orthogonal to each other), respectively.

Experiment

Participant data was collected during a mental rotation experiment as part of a Bachelor's thesis (Raddatz, 2014). The experiment was based on the classic mental rotation paradigm by Shepard and Metzler (1971). In a trial, one out of 16 figures is presented to the participant without any rotation. After 1 second, either the original figure or a mirrored version of it is presented and rotated by either 0, 50, 100 or 150 degrees on the picture plane. The participant must decide whether the presented objects are equal or mirrored variants of each other. To this end, the participants are instructed to mentally rotate one of the objects clockwise until an informed decision can be made if the objects match or mismatch. 6 Blocks of each

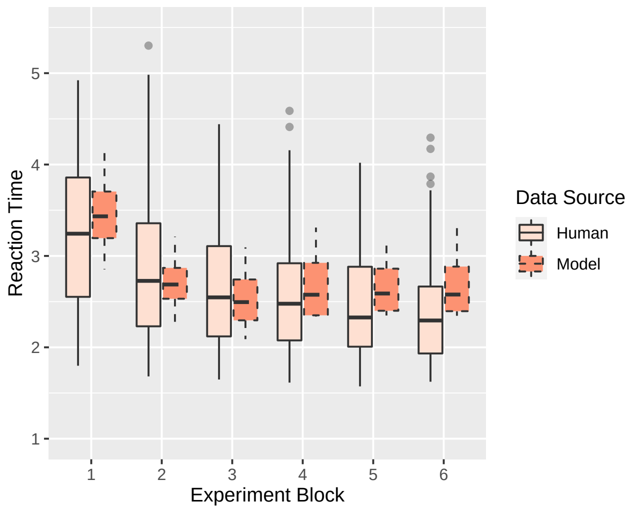

Figure 2: Aggregated human (*leftmost, solid outline*) and model reaction times (*rightmost, dashed outline*) for each experiment block.

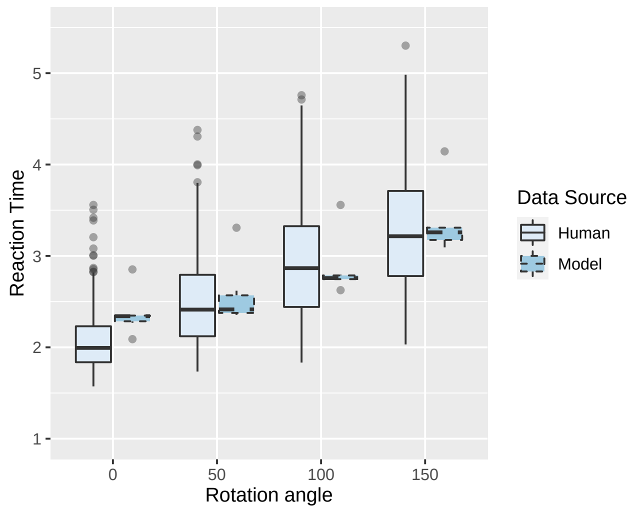

Figure 3: Aggregated human (*leftmost, solid outline*) and model reaction times (*rightmost, dashed outline*) for each rotation angle.

possible trial combination (16 figures * 4 degrees of rotation * 2 types of mirroring = 128 combinations) take place, resulting in 768 trials overall. The cognitive model was designed to solve a simulated version of this experiment.

Mental Rotation Model

By making use of the spatial module's ability for both symbolic and spatial information, the mental rotation task model implements a cognitively plausible approach for human-like solving. The cognitive model follows the process model originally proposed in Just and Carpenter (1976), and follows their proposal of three rough stages –initial search, transformation and comparison, and confirmation. The model offers two strategies, first differentiated by Yuille and Steiger (1982) as ”holistic” comparison (also referred to as ”wholesale”) and ”piecemeal” comparison: if the presented figure is ”known”, meaning the object is sufficiently familiar, the object can be transformed and compared as a whole. On the other hand, if the presented figure is unknown to the solver, meaning it was not seen before or forgotten, it has to be sequentially transformed and compared by its individual features or *pieces*. In the case of mental rotation stimuli, pieces are the respective straight sections formed by multiple cubes, of which each figure has either 3 or 4. Thus, use of a piecemeal strategy explains longer reaction times for “unknown” figures in human trials.

At the start of each trial, the current reference stimulus is presented: both its individual features and the complete object are placed in the environment as visual features visible to the model. First, the model encodes the whole object and attempts a declarative memory query, testing for object familiarity –if successful, the wholesale strategy is initiated. If the presented object can not be remembered, the model waits for the appearance of the target stimulus, which happens one second after the reference stimulus appears. Then, either the whole target object is visually encoded and prepared for the wholesale strategy, or its separate features are visually encoded and considered for the piecemeal strategy.

While solving the mental rotation task, the model rotates the object or parts of the object –depending on the strategy – by a fixed amount of 45 degrees, chosen to be close but avoid equality to the experiment's rotation conditions. After each rotation, a comparison process measures the mean euclidean distance between paired points of the point clouds of the target object with its reference counterpart, resulting in a similarity value. If this comparison results in a similarity higher than a preset threshold, but lower than the last value computed (or is the first comparison for this trial), an additional rotation is planned and executed. If the comparison yields a value higher than the threshold but also a value higher than the last similarity value, the model assumes that a low enough similarity value cannot be reached and gives a ”mismatch” answer. If the similarity value is lower than the threshold, a match of objects is assumed. In the wholesale strategy, the trial is then directly confirmed as a “match”. In the piecemeal strategy, the degrees of rotation necessary to reach this similarity are remembered and applied to subsequent pieces. If all pieces yield similarity values under the threshold, the object is considered a match and a ”match” answer is given. For this experiment, a threshold value of 20 and 45 degrees of rotation per transformation yielded the best results. Additionally, the following parameters were adjusted as follows:

- Latency factor: 0.3 *(default: 1.0)*
- Retrieval threshold: -1.0 *(default: 0.0)*
- Activation noise: 0.5 *(default: none)*

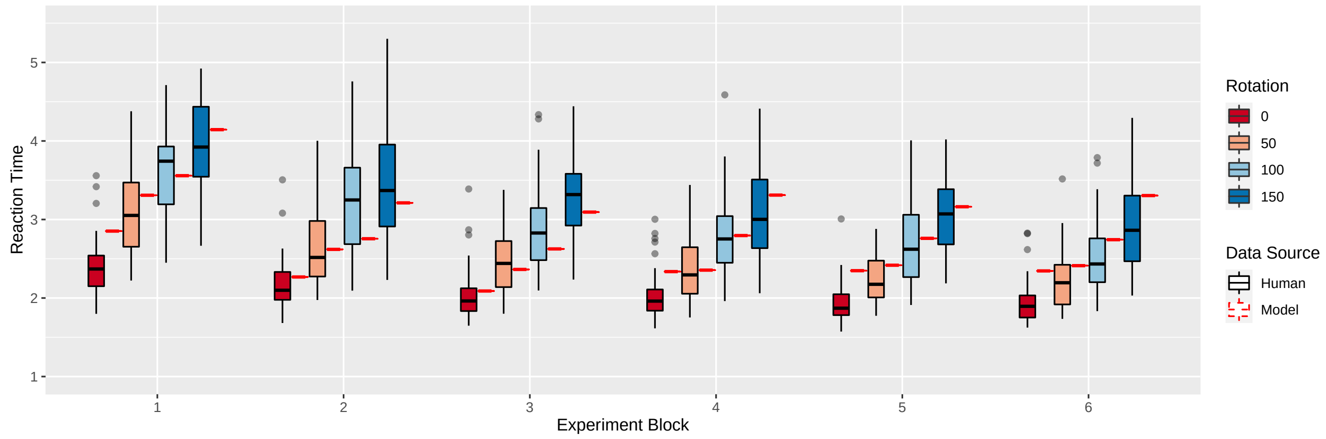

Figure 4: Human reaction times (*leftmost per color, solid black outline*) and model-predicted reaction times (*rightmost per color, dashed red outline*), grouped by rotation condition and experiment block.

- Utility noise: 2 *(default: none)*
- Spatial delay: 0.005 *(default: n/a)*

The aforementioned strategy choice is integrated in the form of a memory retrieval to mimic object familiarity –if the reference stimulus was presented often and recently enough, the model can proceed with the wholesale strategy, otherwise the piecemeal strategy is chosen. Reinforcement learning is implemented in the form of utility learning: model decisions that consistently result in fast and correct task solving will be reinforced and chosen more frequently in subsequent trials.

Results

Both datasets were prepared by Median Absolute Deviation outlier correction. Figure 4 shows reaction times from participant data and model predictions.

Model Data

The model predictions correlate nicely with behavioral data. A strong overall correlation with little deviation to human data was achieved ($r(22) = .92, p < .001$; RMSE $= .23$). More specifically, the influence of rotation disparity on model and human reaction times aggregated over all blocks reached a very strong correlation ($r(2) = .97, p < .05$, RMSE $= .139$) (see also Figure 3), while comparing the influence of experiment block aggregated over all rotations shows a strong correlation ($r(4) = .84, p < .05$, RMSE $= .22$) (see also Figure 2). Overall standard deviation of model-predicted reaction times is close to the original data, but slightly lower ($SD_H = 1.953, SD_M = 1.421$).

Regression Analysis

A linear model was created, gauging the influence of experiment block, rotation disparity and data source (*human* or *model*) on reaction times. The three predictors explained 53.9% of the variance ($R^2 = 0.539$, $F_{47,840} = 23.04$, $p < .001$). Rotation angle significantly predicted reaction times ($\beta = 0.66$, $p < 0.001$), as did the interaction between experiment block and angle ($\beta = -0.29$, $p < 0.05$). Data source has no influence on reaction times ($\beta = 0.02$, $p = 0.43$), implying no significant differences between human and model results. As shown in Figure 4, a linear effect is visible, with increased rotations leading to increased reaction times. Over blocks, reaction times are generally lowered, with a more pronounced effect for higher rotations.

Discussion

Interpretation of Results

The behavioral data collected shows a linear effect of difficulty typically reported in mental rotation studies (Shepard & Metzler, 1971). A decrease of reaction time over the experiment blocks suggests a learning effect that is more pronounced for higher task difficulty, which mirrors results previously reported for a mental folding task (Preuss, Raddatz, & Russwinkel, 2019). The model results show a promising fit to the behavioral experiment data. Aside from a strong general correlation, it accurately models learning over experiment blocks, which validates the implemented strategy choice mechanism based on object familiarity.

Correlation between the two datasets is comparable to results from similar modeling approaches to mental rotation (e.g. Peebles, 2019a). Of note is that our results stem from the reliance on generalized spatial processes instead of mechanisms tailored to the task at hand, giving strong support for the validity of a unified approach.

Open Questions and Known Issues

The spatial module for ACT-R enqueues itself into a line of similar theoretical approaches and implementations. Mental imagery (Peebles, 2019b; Lovett & Forbus, 2013), qualitative reasoning (Forbus, 1984; De Kleer & Brown, 1984), syllogistic representations (Barkowsky et al., 2007), or spatial-visual integration (Laird, 2008) offer alternatives to tackle open questions in spatial research. As of now, our common spatial framework does not challenge these theories, as insight into the nature of the cognitive mechanisms underlying spatial processes is still vague. Further research could increase support for our approach, or dismiss it altogether.

Most design decisions for the spatial module are made under consideration of prior research as outlined above. Still, many of its mechanisms are currently in need of verification. For now, the mental rotation model is the only cognitive model fully realized using this framework. While this model proved successful, additional work on cognitive models for other spatial paradigms is necessary to validate the framework further.

The underlying experimental data was originally collected for an EEG study –therefore, the experimental design was kept simple to reduce unwanted artifacts (i.e. stimuli were only rotated on the picture plane, low overall task difficulty). This restricts the use of these data for several interesting questions in the modeling domain: does mental spatial transformation happen statically and stepwise, or is it dynamic? Is there a number of maximal transformations applicable on a mental spatial object? These issues will be addressed in future study designs.

Outlook

Since ACT-R simulates cognitive functions in a modular fashion, it lends itself to modeling effects beyond behavioral data: a method proposed by Prezenski and Russwinkel (2016) would allow a comparison of ACT-R module activity to EEG data of experiment participants. To this end, components are calculated from EEG data, i.e. clusters of neurons that are frequently active in parallel. In the case of independent component analysis (*ICA*), components with the highest degree of independence from one another are generated, meaning that in theory, cortex areas fulfilling distinct functions are mapped for each participant during task solving. These independent components can then each be associated to ACT-R's modules by correlating brain activity with predicted module activity. This could help verify or falsify the existence and/or location of one or several dedicated spatial area(s). Another promising approach lies in computing principal components of EEG signals for comparison with module activity produced by the cognitive models. A principal component analysis (*PCA*) ranks components by variance explained which then can be associated with activity of specific modules during specific times during task solving (Borst & Anderson, 2015; Tenison, Fincham, & Anderson, 2016). While ICA matching helps localizing specific brain activity, PCA matching allows for temporal correlation. Both methods are currently being tested on data sets created by the mental rotation model.

[Mention of related project omitted for anonymity] In addition to a study on mental rotation, an experiment on a mental folding paradigm (Shepard & Feng, 1972) was conducted and simulated in a cognitive model using the spatial module (Preuss et al., 2019). Applying the spatial module to a related mental spatial paradigm allows for further verification or falsification of its validity and should lead to adjustments necessary for its further generalization. To arrive at a module representing universal spatial cognition, it will be important to follow the constraints dictated by both cognitive architecture and neurobiological plausibility to avoid parameter overfitting.

As the effects of several factors on spatial processing time are yet to be gauged and additional spatial paradigms yet to be implemented on the basis of the spatial module, it currently computes the time necessary for mental spatial transformations on the basis of an admittedly simple multiplication. Other variables influencing the outcome are in consideration to be included in later versions of the spatial module, for instance added noise to reduce the formula's deterministic behavior, increased processing time depending on the number of transformations already applied to the object in the spatial buffer or an upper limit to the transformations applicable in a row.

A follow-up experiment will combine both mental rotation and mental folding into one experimental paradigm. By forcing the use of cognitive folding and rotation processes at the same time, this study and further upcoming work will rely less on lab conditions and move towards real-world applications. Requiring both spatial modalities for problem solving will allow further evaluation of the proposed module's validity.

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