An implementation of Universal Spatial Transformative Cognition in ACT-R

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Abstract

Mental spatial transformation is usually modeled with highly task-specific approaches, allowing high model accuracy and valid explanations for effects in experimental data. These approaches however suffer from overfitting of models to data, resulting in low general validity. Based on neuro-imaging research suggesting a dedicated cognitive system for mental spatial transformation, a theory for universal spatial transformative cognition and its implementation as an ACT-R module is proposed. This spatial module enables the prediction of processing time for mental spatial operations. Concurrently, a mental folding experiment is conducted to gather participant data for model fitting. Our data confirms an effect of transformation difficulty on reaction times often found in related research, as well as learning effects during the experiment. These results form the foundation for ongoing development of the spatial module, especially regarding the influence of transformation complexity on spatial assessments.

Keywords: spatial cognition; cognitive modeling; ACT-R; mental folding; mental transformation

Introduction

Mental spatial manipulation of objects or scenes is a core mechanism of human cognition. In this regard, understanding an object in three-dimensional space allows us to reason and make assumptions about quality, category, function and other attributes associated with it (Kosslyn, 1996). Although mental spatial transformation is often associated with mental imagery, evidence for the distinctness of the two exists. Spatial representations seem to be separable from mental imagery (Knauff & Johnson-Laird, 2002). A study by Gramann (2013) implies the existence of inter-individual differences in spatial cognition, including the proclivity for an egocentric or allocentric reference frame during mental spatial tasks. Mental spatial processing and mental imagery seem to be situated in separate brain areas, respectively: past research of behavioral and neurophysiological data implies pathways for spatial processing as well as a functional distinction between egocentric and allocentric cognitive systems (Nadel & Hardt, 2004).

Different, partially compatible paradigms for mental spatial transformation have been introduced, each proposing factors for the complexity of a spatial transformation. Shepard and Metzler (1971) studied reaction times for the sameness of two abstract 3D objects, of which one is rotated to a variable degree. A linear relationship between angular disparity and reaction time was found. As objects were only required to be mentally rotated however, the explanatory power of this study for general spatial cognition seems limited. A follow-up study measured reaction time during a task based on cube folding patterns (Shepard & Feng, 1972). In a recent variation of this cube folding paradigm (Wright, Thompson, Ganis, Newcombe, & Kosslyn, 2008), a reference object must be mentally manipulated to assimilate its shape to a target object. Reaction time grew linearly with the folding complexity required by the target object. Additionally, higher complexity levels were reported to be unsolvable within the given time limit by most participants, which suggests an upper limit to spatial transformation capacity.

Lotz and Russwinkel (2016) introduced a decay factor for spatial representations. According to the authors, these decaying representations could only be upheld for a short period of time before they required re-encoding by visual or memory processes. In another variant of mental rotation, a study theorized that non-linear reaction time results are caused by the intricacy of the transformations necessary for a correct response (Neely & Heath, 2010). Based on this theory, higher transformation complexity could be a factor especially in demanding tasks. Other possibilities of complexity measures for spatial processing exist, such as object structure (Bethell-Fox & Shepard, 1988), semantics (Smith & Dror, 2001) or familiarity (Bethell-Fox & Shepard, 1988; Smith & Dror, 2001), and potentially many others. So far, no unequivocal data reasonably demonstrates their effect, but these factors should be kept in mind.

Modeling Spatial Cognition

The cognitive architecture ACT-R (Anderson et al., 2004) consists of modules which represent cognitive systems for e.g. visual, imaginal or motoric processing. Cognitive models rely on the interplay of these modules to simulate specific task behaviors and cognitive processes by exchanging information between buffers associated with each module. This approach also allows for the prediction of brain activity, as the neural representation of each cognitive system can be roughly localized in the human brain (Borst & Anderson, 2015).

While ACT-R offers a unified approach for cognitive modeling of mental imagery (Anderson et al., 2004), similar mechanisms are so far not available for mental spatial transformation. Such cognitive systems and their implementation as a module for ACT-R have been proposed (Gunzelmann & Lyon, 2007), but so far not scientifically validated. In this paper, we seek to formulate a theory on mental spatial transformative cognition, namely how effects shown in studies of spatial cognition can be represented algorithmically, and implement it in the form of an ACT-R module. The goals for the module are:

- **Explainability**: known effects in spatial cognition like growing time costs with growing task complexity, differences in spatial strategies and others should be explained by spatial module functions

- **Universal applicability**: the module should support multiple mental spatial transformation paradigms

- **Validity**: as models are able to refer to a unified implementation of spatial cognition instead of using highly task-specific approaches, the overall validity of modeling spatial processes is improved

One of the challenges of modeling mental manipulation lies in correctly predicting the effect of inter-individual differences, for instance in the proclivity for egocentric or allocentric reference frames (Gunzelmann & Lyon, 2011). The proposed addition to the ACT-R architecture should eventually account for these differences by providing the possibility of multiple approaches to spatial transformation. Additionally, identifying the source of effects like cognitive limitations, time demands, inaccuracies and errors is essential for a sufficiently predictive performance of the module.

As a starting point for the development of the spatial module, we chose to conduct an experiment based on the mental folding task developed by Shepard and Feng (1972), in a variation by Wright et al. (2008) as described above. Concurrently, two cognitive models are developed: one using only default ACT-R modules (the *baseline model*), another incorporating our spatial module (the *enhanced model*). The baseline model will rely on default ACT-R capacities with the goal of achieving as close a fit to human behavioral data as is possible with ACT-R's base mechanisms, while the enhanced model will make use of the spatial module described in this paper. Thus, the baseline model will act as a benchmark - if the addition of a spatial module is indeed a reasonable assumption, the enhanced model should reach a significantly better fit while ideally explaining effects that the baseline model can not.

Hypotheses

We expect our experimental results to show a linear effect of task difficulty on reaction time, as previous studies have shown (Shepard & Feng, 1972). Over the course of the experiment, participants should also show learning effects, resulting in shorter reaction times. The enhanced model should subsequently show an improved fit compared to the baseline model while being more cognitively plausible.

Methods

Mental Folding Study

Participants The study was conducted with 45 participants, of which 5 were excluded due to aberrant error rates, reaction times or technical problems, leaving a sample of 40 participants (20 female, 20 male). All participants were selected according to their orientation strategy measured via the Reference Frame Proclivity Test (Goeke, König, & Gramann, 2013) and completed a pretesting battery prior to the mental folding task. Additionally, data from a 64-channel electroencephalogram (EEG) was collected. Participant selection, pretesting and EEG-Data are no further subject of this paper.

Mental Folding Task A computerized version of the mental folding task originally developed by Shepard and Feng (1972) was created and adjusted into a comparison task similar to the task designed by Wright et al. (2008). The mental folding task consisted of reference figures in the form of semitransparent 3D cubes, and 2D unfolded cube templates as target figures, each with two black arrows on their surfaces and a blue square indicating the base, presented on a black background. Each trial started with a one second presentation of a central fixation cross, followed by the display of a reference figure, either on the left or right side of the screen. Subsequently, after one more second, a target figure appeared on the other respective screen side. The participants were asked to mentally fold the template together and to decide then whether the arrows on reference and target match. Judgements on matching or mismatching arrow positions were recorded via button presses on a response pad. Vertically aligned buttons were used with one button for each judgement type. The experiment consisted of 600 trials, subdivided in five blocks. Participants had to take at least one minute breaks between the blocks and were instructed to always fold upwards, starting from the base. Task completion took 60 minutes on average and each participant passed through 10 minutes of training with feedback in advance.

Stimuli Four levels of difficulty were chosen for the task (see Figure 1). The sum of squares carried (*SSC*) during the series of folds necessary to compare the arrow positions determined the level of difficulty, as defined by Shepard and Feng (1972). The easiest level (A) was a direct visual comparison with arrow tips always meeting. The second level (F) required to carry four, the third level (G) five and the fourth level (H) six squares through the folding sequence. Six different template figures with three arrow variations each (for Levels F, G and H: one variation with arrow tips touching, two with arrow tips in different directions) were constructed

Difficulty Level	A	F	G	H
Squares Carried	None	2 + 1 + 1 = 4	3 + 1 + 1 = 5	3 + 2 + 1 = 6
Example Pattern				

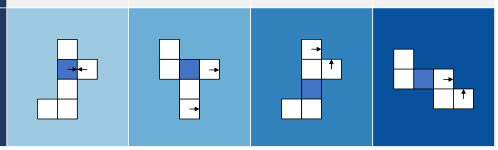


Figure 1: Difficulty levels used in the experiment, based on the classification by Shepard and Feng (1972). Squares carried refers to the amount of squares that need to be transformed to reach an informed decision.

for every level and paired with reference cube figures with either matching or mismatching arrow positions. This resulted in 144 different trials. In order to shorten the length of the experiment to one hour, 24 trials of the mismatch condition were excluded by balanced randomization from each block. Each mismatch stimulus type of each level was shown at least three times over the whole experiment, resulting in 72 match- and 48 mismatch trials per block. The sequence of trials and the presentation sides were randomized in a balanced manner within each block.

Baseline Model

Lacking a spatial module, the baseline model uses memory retrieval as its main mechanism. Spatial structures and results of folding operations are encoded as world knowledge and queried as needed. Cube and folding pattern are visually presented to the model. Arrow directions and base square positions are then saved in a mental representation and used to create folding paths for each arrow on the folding pattern. These paths are then subsequently folded up and the resulting mental images compared to the actual arrow positions and directions on the reference cube. Additionally, a simple instance learning mechanism is implemented, allowing improvement over time.

While the approximation of spatial processes through repeated memory retrieval processes is highly implausible, it represents a reasonable approach using only the standard ACT-R architecture, and thus a benchmark to be improved upon by the enhanced model.

Spatial Module

The spatial module integrates seamlessly into the existing modular structure of ACT-R. Its feature set is chosen with mental rotation and mental folding paradigms in mind, although other applications are possible. In its current version the module supports translation, rotation, scaling and comparison of three-dimensional objects. As it is developed concurrently to subject data acquisition, several design choices are intuitive as of now. Results of upcoming research will be consulted to confirm or improve the proposed module structure.

Structure The module is interfaced by use of its two buffers:

- The *spatial* buffer acts as storage for a mental spatial image of an object, which in turn can be a specific part of a larger object or a group of smaller objects. These objects consist of a three-dimensional representation and optionally of a specific object class, a list of contingently attached objects and a pointer to an origin object, if applicable.
- The *spatial-action* buffer is analogous to the imaginal-action buffer in the way that transformations to the mental representation are handled. It receives and handles transformation requests or queries about the object in the *spatial* buffer.

Point clouds form the structure for three-dimensional representations, as they are versatile and easily transformable through mathematical computation. Each point is formed by xyz-coordinates, allowing objects to be represented with arbitrary level of detail.

Buffer structure and amount were chosen to balance functionality and parsimony - this module setup should allow applicability to all spatial tasks while limiting its complexity and need of resources. This way, in contrast to the approach of Gunzelmann and Lyon (2007), interaction with ACT-R's core module structure is facilitated: as spatial object chunks are standard ACT-R chunks, functionality like object comparison or episodic memory can be achieved through or supported by default modules.

Configurable module parameters are module latency and maximum transformation complexity.

Complexity of Spatial Representations The module observes an upper limit on the number of transformations applicable to the object. If this number is reached, no further transformations will take place and the module will return an error. This limit is an exploratory account of effects showing that for tasks of high difficulty, a jump in reaction time occurs, breaking the linear pattern (Shepard & Feng, 1972). The authors assume that these jumps reflect re-encoding processes - to continue the task, the preliminarily transformed object needs to be harvested from the buffer, memorized and subsequently either recalled from memory or visually re-encoded again. Further research will try to validate this assumption.

At the moment, the upper limit of subsequent object transformations defaults to 4, in line with the instantiation fingers (or finsts) of the declarative and visual modules that work as similar limitations. If a valid transformation is requested on the object in the spatial buffer and the upper limit is not reached, a complexity equation is consulted to compute the

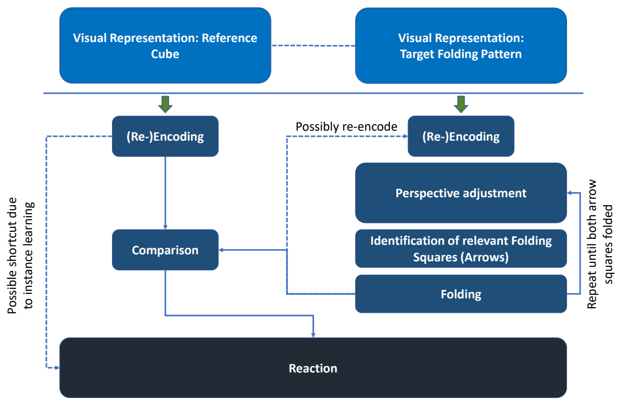


Figure 2: A rough outline of the process underlying the enhanced model. Visual representations get encoded, then relevant surfaces of the folding pattern are mentally folded up and subsequently compared to the reference arrow positions and directions.

time delay required for the operation. As data of mental spatial studies (e.g. Shepard and Metzler (1971), Shepard and Feng (1972)) shows a linear relationship between the discrepancy of the spatial object to its required transformation state and reaction times of human participants, a linear equation of the form $f(x) = b + mx$ is used as a basis for the complexity equation. We assume the intercept b is given by ACT-R's default mechanisms such as production firing or the forming of mental representations. The rest of the equation (i.e. factor m) is proposed to be as follows:

$$C_{request} = F * M * x * N^2$$

- F: a latency factor, set as a module parameter. Its default value will be fit based on current experiment data.
- M: a compensation factor used to equalize discrepancies between transformation types like rotation or translation. Potentially depending on the specific function called, this factor equals 1 for now.
- x: the change value for the transformation, i.e. degrees, distance units or others.
- N: the current number of transformations applied to the mental spatial object since it was put into the spatial buffer. This implements research by Neely and Heath (2010), implying that reaction times grow with increasing transformation complexity.

Capabilities of the Module The spatial module is able to translate, rotate and scale spatial objects consisting of point clouds in 3D space. For comparison between two spatial objects, so far two operations are available: A simple comparison is implemented that compares the mean euclidean distance between point pairs from two point clouds. If the point clouds have unequal sizes, the distance from the spare points to the origin substitutes the missing pairs. For instance, an object compared to itself would return a mean euclidean distance of 0, while deviating objects return larger values depending on their scale and significance. Furthermore, a computation of the angle between vectors is implemented to allow for the comparison of e.g. reference and target arrows.

The module offers these tools for modeling mental spatial transformation, however certain task-specific operations like reacting to specific thresholds or perception of the spatial objects still need to be implemented on a model level.

Enhanced Model

An enhanced model for the mental folding task that incorporates the spatial module is currently in development. The underlying process is based on the baseline process model, but instead of memory retrieval processes, spatial information is now processed by the spatial module, which calculates the time needed for each spatial operation based on the above equation. Each square of the folding pattern is now foldable in 3D space, while arrows are represented as direction vectors. Once all relevant surfaces have been folded to their respective cube positions, these direction vectors are compared to the reference arrows and used to form a decision. A process diagram of this model is depicted in Figure 2.

As the enhanced model foregoes memory retrieval processes for spatial operations, it exhibits stronger cognitive plausibility, as forming representations through declarative knowledge is unlikely to occur in spatial problem solving. Additionally, the resulting process model is less rigid and allows for easier backtracking, required for modeling phenomenons like loss of concentration or validation.

Comparison to Experiment Data

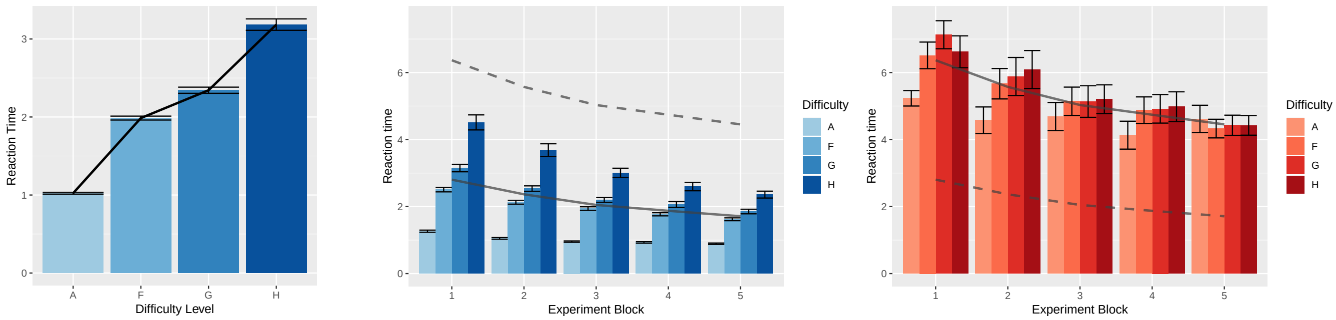
The models are compared to participant data through correlation and root mean square error (RMSE) of averaged reaction times and model output, respectively.

Results

Experiment Data

Behavioral data was analyzed to investigate effects of the factors Difficulty Level and Experiment Block on participant reaction time. Only trials with correct responses were selected for analysis. Trials with reaction times lower or higher than 2 standard deviations from the levels mean within each participant were considered outliers and therefore excluded from further analysis.

A two-way ANOVA with the within-factors Difficulty Level (A, F, G, H) and Experiment Block (1, 2, 3, 4, 5) was conducted on logarithmized reaction times. ANOVA results, adjusted per Greenhouse-Geisser, display significant main and interaction effects of the factors Difficulty Level and Experiment Block on reaction time (Difficulty Level: $F_{1.74,67.96} = 282.86, p < .001$; Experiment Block: $F_{2.16,84.22} = 144.17, p < .001$; Interaction: $F_{5.94,231.84} = 12.57, p < .001$). Reaction times increased with increasing



(a) Effect of Difficulty Level

(b) Participant Reaction Times

(c) Model Reaction Times

Figure 3: Error bars depict 95% confidence interval. **(a)** Reaction times in seconds averaged over participants and blocks, showing the mean effect of difficulty level. Level *A* requires no folding operation. The sums of squares carried necessary during folding are 4 in Level *F*, 5 in Level *G* and 6 in Level *H*, respectively. **(b)** Average participant reaction times in seconds per Difficulty Level and Experiment Block. Black solid line denotes the learning effect, averaged over levels of difficulty. Dashed line shows model learning effect for comparison. **(c)** Model reaction times in seconds per Difficulty Level and Experiment Block. Black solid line denotes learning, averaged over levels. Dashed line shows human learning for comparison.

level of difficulty. Tukey-corrected post-hoc comparisons reveal that the increase in reaction time with increasing level of difficulty is significant in all blocks, with the exception of the difference between difficulty Levels F and G which is only significant in the first two experiment blocks. Overall the ANOVA results seem to imply a learning effect that is especially pronounced for higher difficulty levels. Means and standard deviations are summarized in Table 1. The latency factor parameter of the spatial module was fit based on the averaged reaction times for each difficulty level (see Figure 3a), suggesting a factor of around 0.6 per necessary folding operation.

Model Data

Baseline Model The baseline model output is sufficiently similar to participant data (see Figures 3b and 3c). Due to its mechanisms being based on world knowledge retrieval instead of actual spatial processes, model reaction times are uniformly higher than for participants. While a comparison of model and human reaction times over the factor difficulty showed no significance ($r = .89, p = .11$ with an RMSE of 3.14), a comparison over experiment block showed a high correlation with high significance ($r > .999, p < .001$ with an RMSE of 3.09).

Discussion

Discussion of Results

Both human and model data show a clear improvement over time, correlating highly and showing a learning effect that seems well explained by instance memorization. This suggests an important role of pattern memorization for improvement in spatial tasks.

The effect of task difficulty - as in the sum of squares carried over all necessary folding operations to obtain the correct arrow positions and directions - is clearly pronounced in the experimental data. The baseline model shows a similar influence of the difficulty factor in its output, but shows no correlation to the human data. Interestingly, reaction times for the highest difficulty setting seem to diverge from the linear influence of required folding operations, implying other factors. This might support the aforementioned idea that with more complex mental spatial transformations, re-encoding processes take place (Neely & Heath, 2010).

The data also shows a slight decrease of variance in the reaction times for higher difficulty levels that grows smaller over the course of the experiment (Figure 3b). This variance seems to be within-subject, meaning that solvability of the puzzles in higher difficulties differed strongly for unexperienced solvers, but gradually improved.

Revisiting our original hypotheses, we found a mostly linear effect of task difficulty, with slightly longer reaction times for the highest difficulty level at the start of the experiment than a linear relation would suggest. Learning effects over the course of the experiment in the form of decreasing reaction times were also found. The baseline model showed highly similar learning effects, but remains much slower than human participants and relies on cognitively implausible mechanisms for mental spatial transformation.

Open Questions

The specifics of the spatial module are chosen for simple integration into the existing module structure of ACT-R, its functional requirements and buffer parsimony. These might be challenged by upcoming neurophysiological results of human problem solving in mental folding and rotation tasks. Potential consequences range from showing the existence of multiple systems to a lack of evidence for a dedicated spatial system altogether.

With the claim of modeling universal mental spatial cognition, information from several paradigms needs to be evalu-

Block	Difficulty	Mean	SD
1	A	0.17	0.35
1	F	0.84	0.39
1	G	1.02	0.49
1	H	1.32	0.59
2	A	-0.01	0.33
2	F	0.67	0.40
2	G	0.81	0.47
2	H	1.08	0.63
3	A	-0.10	0.32
3	F	0.58	0.40
3	G	0.66	0.49
3	H	0.91	0.60
4	A	-0.13	0.34
4	F	0.48	0.41
4	G	0.57	0.53
4	H	0.76	0.60
5	A	-0.17	0.34
5	F	0.40	0.41
5	G	0.47	0.51
5	H	0.69	0.55

Table 1: Mean and standard deviation of logarithmized reaction times by Experiment Block and Difficulty Level.

ated and used to fit the spatial module. However, it will still need to be falsifiable - changes to the module need to be done in a way that do not introduce task-specific information, but try to make as few general assumptions necessary to be able to interpret as much spatial processing as possible.

The presented complexity function should work well in the context of mental folding, but its applicability to other spatial paradigms (e.g. non-transformative or non-object-oriented tasks) is still unexplored. While it is based on past research on mental transformation processes, a plethora of amendments or alternatives to the equation is conceivable.

A central issue inherent to the object representation lies in the omission of surface textures. Many paradigms require access to interpretable texture information like arrows, numbers, colors etc. While some features can be encoded as an additional object or point cloud information, this approach is highly restrictive.

The necessity for an equalizing factor for different transformation modalities is unclear. For example, rotation and translation can be reasonably assumed to have different effects on reaction times due to their handling of input as degrees or distance units, respectively. On one hand, a factor specific to the transformation modality could offset this disparity. On the other hand, translation can be interpreted as being based on view angle instead of arbitrary distance units, allowing a closer comparison to rotation. Differences in modalities may not just arise from a disparity in change value however, but from their application difficulty or their neurophysiological basis as well. Additionally, a differentiation between transformations changing the object and those simply changing its perceived orientation could be necessary - a simple rotation seems less resource-intensive than folding parts of an object and subsequently influencing its form or function. In this regard, reference frame proclivity seems especially informative.

Work on the enhanced model is currently ongoing. A challenge remains in finding an optimal ontology for spatial objects, able to represent both internal (e.g. single aspects of an object like cube faces or physical connections between objects) and external (e.g. comparisons of objects or measures of object sameness) relations in and between objects, and adjusting both spatial module and model accordingly.

Outlook

The proposed spatial system is developed in parallel to research into mental spatial transformation. As such, in addition to being subject to change, many details of the implementation are still unclear and highly exploratory. Data from current and future research will aim to provide answers and solutions to these challenges.

On completion, the enhanced model will serve as a first testbed for the spatial module as well as a competitor for the baseline model regarding data fit. Altogether, it forms an important landmark for the validation or falsification of the assumptions laid out in this paper. While spatial reference frame proclivity seems to be an important inter-individual trait for the prediction of performance in mental spatial transformation tasks, it is unclear how spatial processing, and a potential implementation thereof, differs between egocentric and allocentric perspective takers. With the possibility of following distinct neural pathways, a spatial module incorporating this distinction could be comprised of a structure far different than the one described here, e.g. with additional buffers as originally proposed by Gunzelmann and Lyon (2007). This issue will be explored in-depth based on forthcoming imaging data for spatial transformation tasks, with the module being adjusted accordingly.

Upcoming research will incorporate data from a mental rotation study into the spatial module. The additional evaluation of available EEG and eye tracking data for both mental folding and mental rotation will give insight into the functional localization of specific spatial brain functions and improve process models for mental spatial transformations. To enforce the module's universality claim, additional paradigms for spatial tasks like mental scanning or spatial navigation could be investigated in the future.

Acknowledgments

This research is financed through the German Research Foundation (DFG), as part of project #396560184. The authors would like to thank Klaus Gramann for his supervision of the Experiment.

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