Comparison of two cognitive models (LISA and Casimir) with regards to their mental spatial knowledge processing

Hermann Ritzenthaler

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Abstract

In this paper the two cognitive models, LISA and Casimir, will be described and compared to each other with regards to their ability to describe human spatial knowledge processing. Therefore the theories behind the models will be described as well as their implementation. Afterwards the two models are compared with the help of two experiments carried out.

1 Introduction

Spatial knowledge processing describes the process of how humans order objects, when they learn about their locations or their relation to each other. LISA and Casimir are two cognitive models that are trying to explain how human spatial knowledge processing works. This can be topological relations, such as "Paris is part of France", directional relations, like "France is west of Germany", or even relations that describe the relationship of two objects, like "John loves Marry".
Both models describe how spatial knowledge processing in the human brain works and try to answer the questions: how does the human brain remember newly learned things as well as how humans are able to reconstruct knowledge from experienced situations.
In the following sections the theories behind LISA and Casimir will be described.
If two propositions are given, in the form of "A is north of B" and "B is north of C", both models should be able to find out which relation holds between A and C and infer the proposition: "A is north of C" as most humans would infer that too.

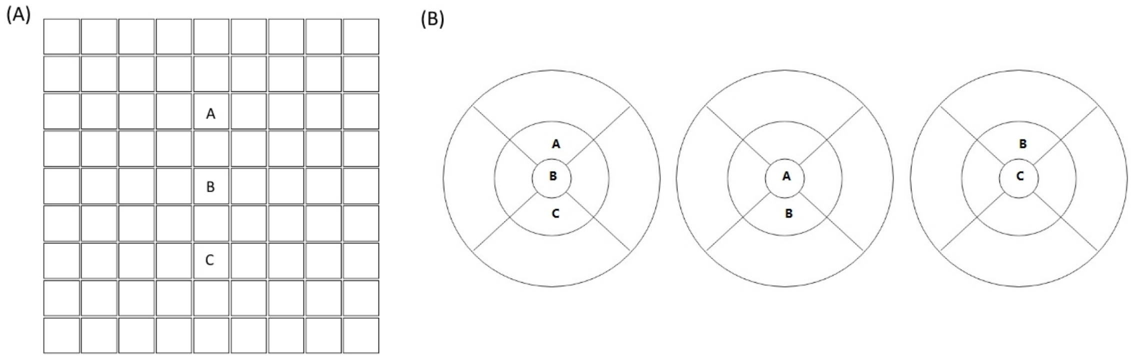

Figure 1: Results for the two cognitive models: (A) LISA and (B) Casimir, after inserting the two propositions "A is north of B" and "B is north of C".

In order to compare both models, first the existing implementation of LISA, implemented by Hummel & Holyoak in 2003, was tested for its ability to solve the kind of question described in figure 1. Because this implementation is not suitable to solve this kind of question, the mental array module, which isn't part of the original implementation, was newly implemented in the following. Afterwards the cognitive model Casimir described by Schultheis & Barkowsky (2011) was implemented as well [Schultheis, Barkowsky (2011)].
Two experiments were designed by Ragni & Friemann in order to describe how humans process spatial knowledge. In the first experiment the participant will learn two premises such as "A is

north of B" and "B is north of C", and then the participant should answer which relation holds between A and C. In the second experiment the participant was told four premises. Afterwards, the participant was told again four, this time different premises to which the participant should say whether these are true or false.
Afterwards LISA and Casimir will be analyzed and their ability to solve problems like the one described by figure 1 will be reviewed. Their advantages and disadvantages of describing human spatial knowledge processing will be described as well. Finally, both models are compared with each other and a short conclusion is made.

2 LISA

Introduced by Hummel & Holyoak, LISA (Learning and Inferences with Schemas and Analogies) was implemented to describe how the human brain processes spatial knowledge [Hummel, Holyoak (2001)].
The way LISA tries to achieve this is by representing objects and their relations as nodes, that are able to fire events in order to activate different nodes. The firing of events more or less represents neurons and their firing in the brain.
LISA stores knowledge in a tree like structure. Human mental representations try to represent relations and the binding of objects to a specific role of this relation [Doumas, Hummel (2005)]. Therefore LISA maps a sentence like "John loves Marry" to objects and relations so John would be mapped to the role of the lover and Marry to the one beloved.
LISA has a small own self-supervised learning algorithm to learn analogical mapping [Hummel, Holyoak (2005)].
Analogies are a special kind of similarity [Holyoak (2005)]. Normally, analogies describe different situations, in which the objects recognized in one situation can be mapped to objects in the other situation in some regards. Finding analogies between two similar situations is a main part of human knowledge processing as described by LISA. In order to solve problems the human brain tries to recall similar situations, because similar situations tend to be solved similarly [Goldstone, Son (2005)]. Therefore the brain tries to map relations and objects of the problem to an already lived through situation. In order to understand the human knowledge processing and its underlying processes LISA was introduced. LISA tries to explain the process which is happening in our brain when it tries to learn new things or how it tries to recall learned things.
Because spatial reasoning is similar to transitive relation, such as "larger than" or "smaller than", LISA is also able to describe spatial relations such as "above" or "left of".
A core concept of LISA is the MAM (Mental Array Module), which is the module, that maps objects and their relation to values or locations in a spatial mental array. Furthermore, LISA is able to describe additional information about the objects and their relations to each other.

2.1 LISA Workflow

Knowledge in LISA is represented in a tree like structure. Each story or problem is described in an analog, which is a collection of multiple propositions.
In figure 2 the proposition "England is north of France" is visualized. Predicates and objects have semantic units, which also can be shared among the different predicates and objects. The object "France" can have multiple semantic units, such as "country" or "European", which are shared with the object "England". The predicate "north" maybe has the semantic units "cold" or "cardinal direction" and could share the semantic unit "cardinal direction" with the predicate "south".
When the proposition "England is north of France" becomes active, LISA will fire events through that proposition. So next the sub-proposition will become active. Notice, that these sub-propositions are different. For "John loves Marry" as a proposition, we can have "John + love1" and "Marry + love2" as sub-propositions. This means, that John is the lover and Marry is the one beloved, and being a lover or being the beloved can be a completely different thing.
Multiple propositions are connected more or less via shared semantic units. In figure 3 it can be seen that multiple propositions are connected via the semantic units, which describe predicates and objects in the propositions. LISA will fire events through a proposition. Therefore also other propositions can become active, through the shared semantic units. This happens, because events can be fired through different propositions, connected by shared semantic units. So when the

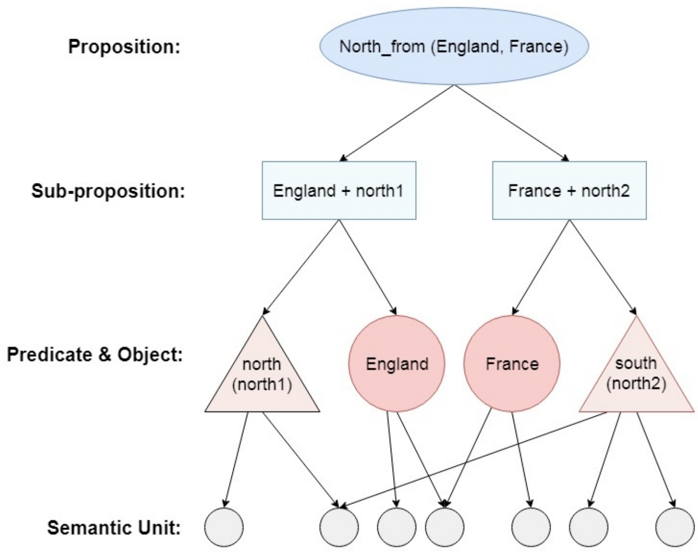

Figure 2: LISA's representation of the single proposition "England is north of France", which is divided in proposition, sub-propositions, predicates, objects and semantic units.

proposition "England is north of France" becomes active, because of shared semantic units between England and Egypt, maybe because both of them are described as countries in the shared semantic units, also the proposition "Egypt is south of France" could become active.
The reason, that both propositions will become active the same time, represents that both propositions are somehow similar. This similarity can be used to inherit more knowledge from one of the propositions. In order to map objects to values, or in this case, directions, LISA has a mental

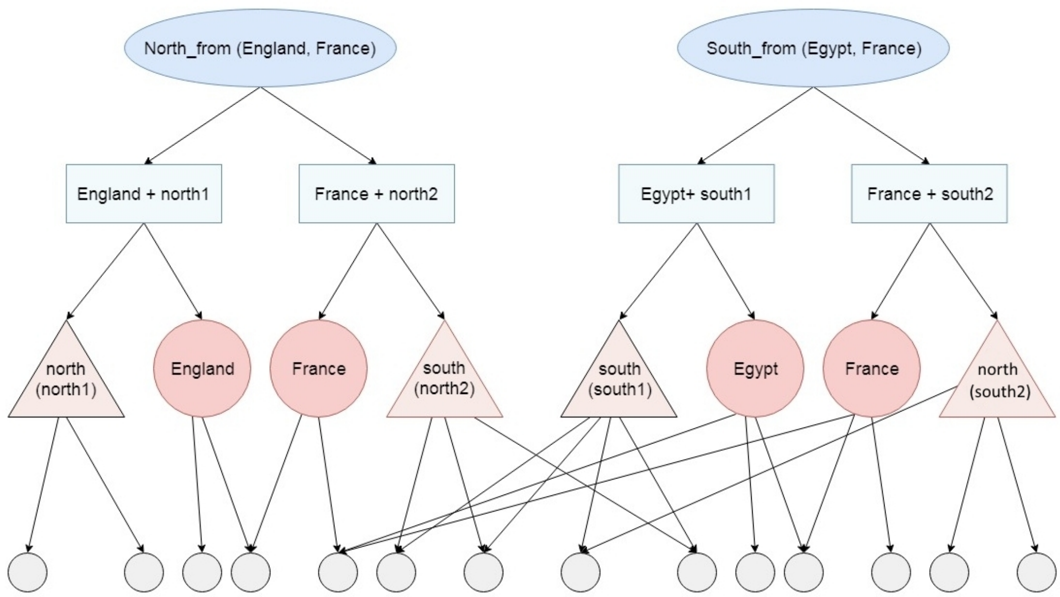

Figure 3: LISA's representation of multiple propositions "England is north of France" and "Egypt is south of France", that share semantic units.

array module (MAM). This array is used to map objects to specific locations in a spatial array.
In figure 4 LISAs representation of the spatial array is visualized. The mental array module consists of the predicates: greater agent, greater referent, less agent and less referent. These predicates are used to save objects to values for propositions such as "A is greater than B". In this example LISA will be able to map different countries to locations on the map. In order to do that, the mental array module could use the predicates: north agent, north referent, south referent or south agent.

The mental array module is more or less an analog itself. So it is connected via shared semantic units to other analogs. The semantic units, that the mental array module shares with other analogs could shared by the predicate "north agent" and predicate in an analog describing that "A is north of B". With help of the mental array module the objects in the analog can be mapped to specific locations in the spatial array.
The reason the MAM is connected to other analogs in the LISA representation, is that whenever a proposition becomes active, which for example describes the direction from England to France, we want to remember the relation of these two in a spatial array. When a second proposition becomes active, which describes the direction from Egypt to France, we want to inherit the relation between England and Egypt. So when these propositions become active, through the semantic units we store these relations in the spatial array.

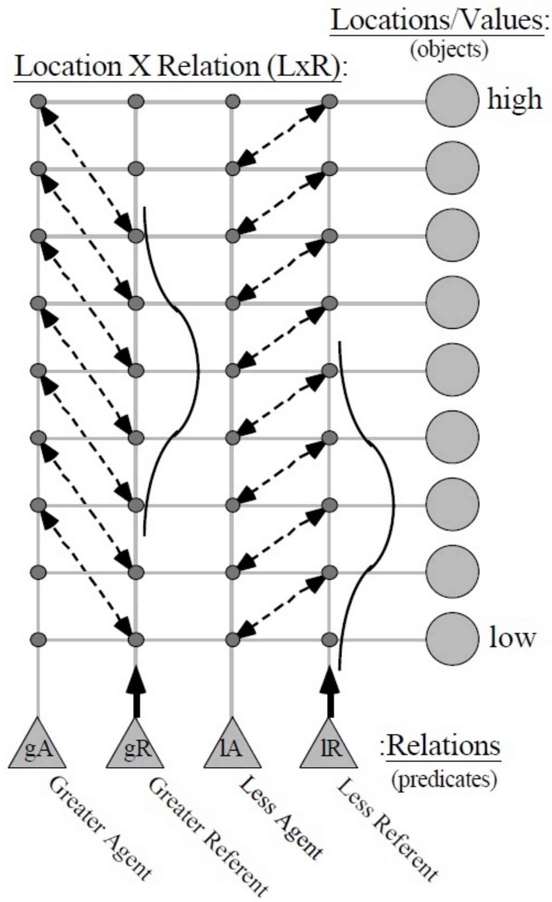

Figure 4: LISA's representation of its mental array module. The mental array module maps objects to values on a scale from high to low. Each object can be the agent or the referent of a relation (gA, gR, lA or lR). The object will be mapped to a value determined by a Gaussian distribution (indicated by the two curves). [Hummel, Holyoak (2001)]

2.2 LISA Implementation

There is an implementation from Hummel & Holyoak made in 2003, which implemented the logic of LISA and simulates LISAs analogy mapping as well as its creation of inferences.
LISA not only finds analogies between objects and their relations such as "John loves Marry" and "Marry loves Chocolate", but also for propositions such as "England is north of France" and "France is north of Egypt".
In order to let LISA run a simulation, two analogs need to be defined. One of the analogs is the driver, one is the recipient. For example if the driving analog consists of "England is north of France", "Egypt is south of France" and "England is north of Egypt" and the recipient analog of

"Sweden is north of Germany" and "Germany is north of Italy". LISA hopefully finds a mapping between the two analogs and infer that Italy is in the south of Sweden.
In the following table it can be seen how these analogs need to be defined for LISA to understand and process them:

Analog1	Analog2
Defpreds North 2 cardinal-direction cold up ; South 2 cardinal-direction hot down ; end; { def preds Defobjs England country UN-member European cold ; France country UN-member European ; Egypt country UN-member African hot ; end; { def objs DefProps P1 North (England France) ; P2 South (Egypt France) ; P3 North (England Egypt) ; end ; { def props done ;	Defpreds North 2 cardinal-direction cold up ; South 2 cardinal-direction hot down ; end ; { def preds Defobjs Sweden country UN-member European cold ; Germany country UN-member European ; Italy country UN-member European hot ; end ; { def objs DefProps P1 North (Sweden Germany) ; P2 North (Germany Italy) ; end ; { def props done ;

Table 1: Definition of two analogs, consisting of three respectively two propositions. These analogs, written in a file, can be used to be simulated by LISA, in order to find analogies and inferences.

After running the LISA simulation, LISA inferred the proposition "Italy is south of Sweden" for the second analog.
The experiments performed by Ragni & Friemann were not compatible to describe by the LISA implementations. LISA tries to infer propositions, which holds for an analog, but this just can be done if a driving analog is given to LISA, from that LISA can learn. For these experiments however, no driving analog was defined, therefore LISA wasn't be able to infer new propositions.

2.3 LISA Mental Array Module

Because the LISA implementation from Hummel & Holyoak does not have a mental array module, which is a main part of spatial knowledge processing in LISA, LISA's Mental Array Module was implemented as a single module to simulate the mapping from objects to locations.
In order to use the mental array module for spatial knowledge processing, the mental array module as explained by Hummel & Holyoak (2001) [Hummel, Holyoak (2001)], was adjusted to be able to process two dimensional data, which is described by relations, such as: north, south, west and east.

In figure 5 it can be seen, how the mental array module of LISA was realized in order to be able to handle two dimensional data. This two dimensional data are in this case cardinal directions. The spatial array is realized as a grid, were each point represents a location from north to south and west to east.
When a new proposition is given to LISA such as "Red is south of Yellow", LISA will use a Gaussian distribution, which chooses a location on the grid, where the object most likely should be mapped to. In this case LISA will most probably choose the location (5,7) for red and (5,5) for yellow. "Purple is north of Yellow" as the next proposition will recognize that the referent of that relation (Yellow) is already mapped to a location in that grid. Because of that, Purple will be mapped to (5,3). This will happen due to the mapping from each cell in the grid to another based on LxR units introduced in Hummel & Holyoaks (2001) paper [Hummel, Holyoak (2001)]. As the next proposition in our example is "Purple is southwest of Green", LISA once again will recognize, that an object of the relation is already mapped to a location in the grid. In this case

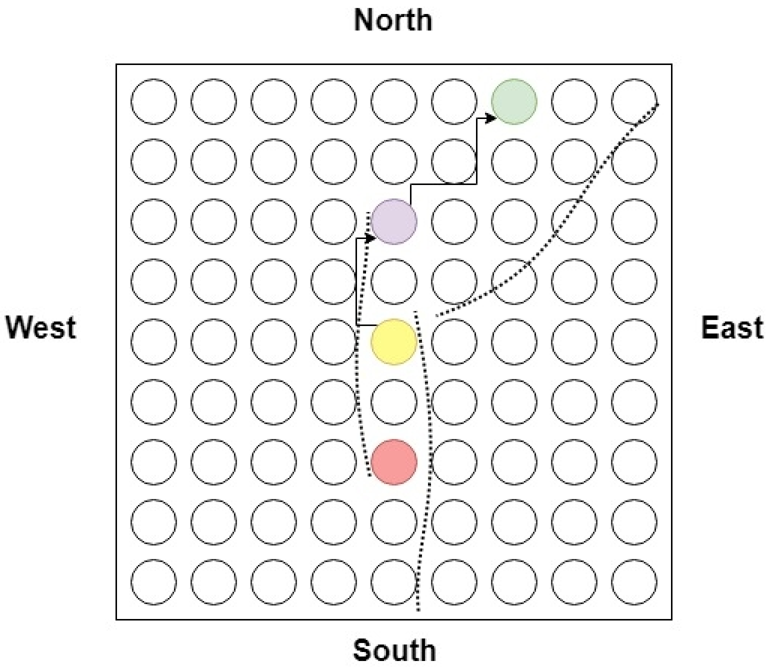

Figure 5: Visualization of LISA's mental array module, extend to two-dimensions, in order to describe north, south, west and east. LxR (indicated by arrows) and gaussian distributions (indicated by dotted curves) were adjusted to the two-dimensional space.

the agent of that relation (Purple) is already mapped to (5,3) and so LISA will map Green to (7,1) based on the calculated LxR units.
In order to be able to analyse the implemented module the user can try out different settings in the simulation. LISA MAM Simulation is able to change the size of the grid as well as the LxR unit distance between two locations. This LxR unit distance can be differently calculated for marked and unmarked relations but does not need to. LISA normally distinguishes between marked and unmarked relations. Unmarked relations are for example: "A is better than B". The associated marked form of that relation is "A is worse than B". Humans tend to map objects on different locations, depending if the relation is in the marked or in the unmarked form. In this implementation of the mental array module of LISA, it is possible to let the simulation distinguish from unmarked relations (main cardinal directions) and marked relations (intercardinal directions). In the paper from Hummel & Holyoak (2001) there is no information, what happens if LISA calculated a location for a new object based on the LxR units, but this cell is already blocked by another object [Hummel, Holyoak (2001)]. Humans tend to create their own preferred model of a situation, if there are ambiguous ways to order the objects [Hummel, Holyoak (1997)]. But if such a case happens, it was decided that LISA will look for the next empty cell to place that object, because on average humans tend to map objects to a location according to the first free fit principle [Ragni, Knauff, Nebel (2005)].

2.4 Simulation Results

To compare multiple settings of this implementation of LISAs mental array module different models were described. These models were used to solve the tasks of the experiment that was carried out. For a detailed comparison of the models the ccobra library was used. The answers of the participants were compared to the answer the LISAs MAM simulation would return for each task. For each task in the experiments the simulation of LISAs MAM will create and fill its spatial array, based on the premises given in each task of the experiment. In order to find out which relation holds between two objects, the angle between the two objects was calculated and compared to the angle of the main and intercardinal directions. The direction, which had the closest angle was chosen.

For each of the two experiments eight models were defined and compared to each other via the framework ccobra. In the following tables and figures the parameters and results for the models can be found:

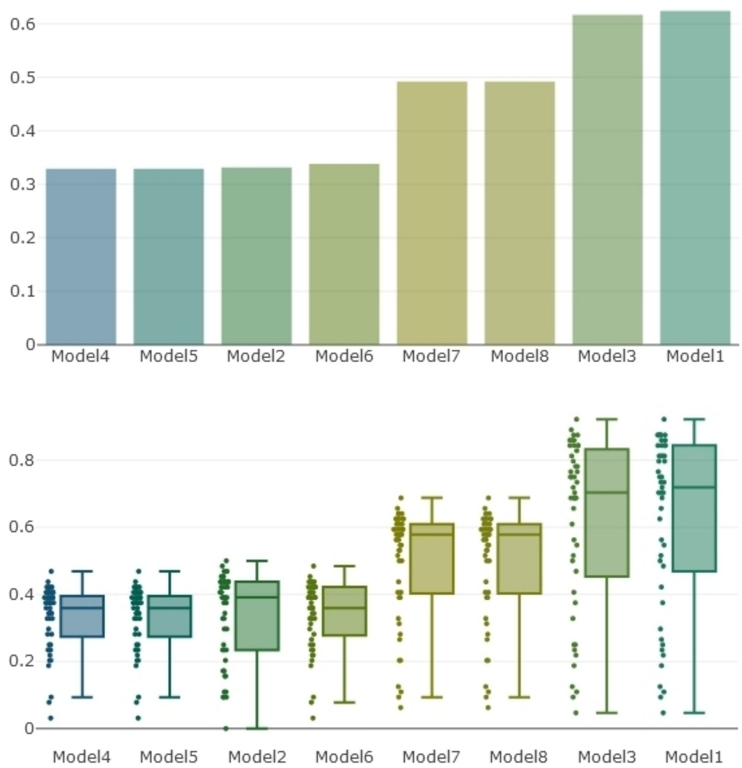

Figure 6: Results of LISAs mental array module simulation for experiment 1

	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
Grid size	9	9	9	21	9	9	9	9
Unmarked relation distance	2	2	2	3	2	2	1	1
Marked relation distance	2	2	2	2	1	1	2	3
With Random	No	No	Yes	No	No	Yes	No	No
Incl. intercardinal directions	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes

Table 2: Models, compared in the LISAs mental array module simulation for experiment 1

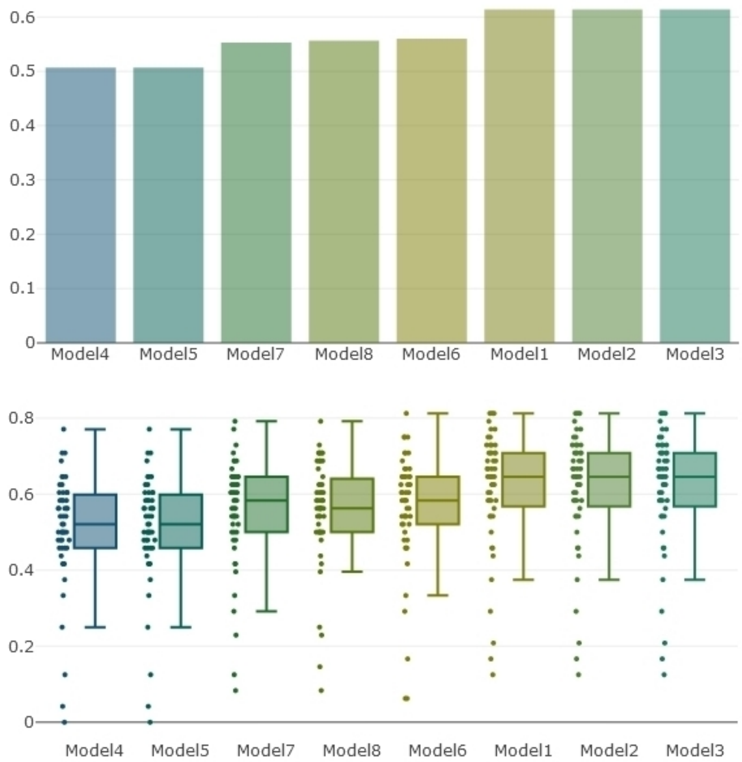

Figure 7: Results of LISAs mental array module simulation for experiment 2

	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
Grid size	13	21	31	7	31	21	21	21
Relation distance	2	4	7	2	10	5	5	5
With Random	No	No	No	No	No	Little	Medium	High

Table 3: Models, compared in the LISAs metnal array module simulation for experiment 2

2.5 LISA Discussion

As previously mentioned, the original LISA implementation is not capable of solving tasks such as "Sweden is north of Germany" and "Germany is north of Italy", which relation holds between Sweden and Italy and infer the proposition: "Sweden is north of Italy". In order to solve that kind of task, the original LISA implementation needs a driving analog from which LISA can learn from and which helps LISA to infer a correct proposition.

The reason the original LISA implementation is not able to solve that kind of task, is that it is missing the mental array module. With the mental array module LISA was able to map objects to locations and therefore able to infer new propositions.

The implementation of LISAs mental array module, was quite simple. The extension to two-dimensions was straight forward and in order to be able to test out different settings, multiple parameters were added to the simulation. Even though most of the implementation details were relatively well specified in the paper of Hummel & Holyoak (2001), one or other question came up. The question about the size of the spatial array as well as the parameters for the Gaussian distribution were not exactly specified by Hummel & Holyoak (2001) [Hummel, Holyoak (2001)]. As a result the size of the grid as well as the parameters for the Gaussian distribution can be freely chosen in the simulation. For the Gaussian distribution two relevant parameters need to be set: the standard deviation and the amount of times an activated event would fire. The more often an event is firing, the more likely the object will be placed closer to the mean of the Gaussian

distribution.
The most important question that came up was: can cardinal or intercardinal directions divided into unmarked or marked relations such as "better than" and "worse than"?
Accordingly to the principle that humans prefer main cardinal directions over intercardinal directions, the main and intercardinal directions were divided up in unmarked and marked relations [Schultheis, Bertel, Barkowsky (2009)]. However, it is also possible to run the simulation without a different treatment of main and intercardinal directions.
After all objects were mapped to a location in the spatial array, the biggest problem is to find out which relation holds between two objects in the spatial array. To solve this problem, the angle between the two objects was calculated and compared to the possible cardinal directions. This method leads to usable and comparable responses, but it probably does not describe how humans would infer a relation between two objects in their mental spatial array.

3 Casimir

Casimir (Computational Architecture, Specification and Implementation of Mental Image-based Reasoning) is a newer model created by Schultheis & Barkowsky (2011) to improve modeling of human spatial knowledge processing [Schultheis, Barkowsky (2011)].
A key assumption of Casimir is, that spatial knowledge processing often uses spatio-analogical representation structures. Casimir consists of three main modules. One one of these modules is the long term memory (LTM), where stored knowledge can be re-accessed, when needed to solve a certain task. The working memory (WM) is the main module of Casimir, which tries to combine spatial knowledge, that can be retrieved via memory or that is learned from the current situation. The third main part of Casimir is the diagram integration module, which helps to visualize the internal process from Casimir and expose them and visa versa.
In the following sections this new model will be described and its ability to describe human spatial knowledge processing will be compared to LISAs.

3.1 Casimir Workflow

As already mentioned before, Casimir consists of three main components, which interact with each other. Each of these modules will be described in an own subsection. The components and it's interactions can be seen in figure 8.

Figure 8 describes the workflow of the knowledge processing done by the Casimir model. The moment a new information arises, Casimir will try to receive corresponding knowledge from the LTM. In order to find corresponding already learned knowledge about a certain situation, Casimir will search along a knowledge tree, that represents the objects and relations that are already stored in its LTM. After retrieving multiple spatial knowledge fragments, Casimir tries to create an activated representation of the knowledge fragments, which means it tries to accumulate different knowledge sources and fragments.
With this accumulated knowledge fragment Casimir creates a mixture of a spatial and a visual mental image. The more information Casimir has about the situation, the more visual the mental image will be. After the conversion of the activated representation of knowledge to the spatio-analogical representation, Casimir tries to inherit more knowledge of the situation by exploration. The inherited knowledge will be used to update the activated representation of knowledge as well as will be stored in the LTM.
The spatio-analogical representation of knowledge is represented as a mixture of a spatial and a visual mental image. The spatio-analogical representation uses a scaleable presentation of structure, which means it will add new learned objects and relations in order to use them from now on. For example, when Casimir learns that "Germany is east of France", it will add the category of relation: "direction", the concrete directional relation: "east", the concrete objects: "Germany" and "France" to its knowledge base.
The implementation of Casimir in the following chapters of this project, will differ from the workflow explained by Schultheis & Barkowsky (2011) in some points [Schultheis, Barkowsky (2011)]. This is done because the paper does not fully describe every part of the workflow exactly and how it could be implemented. More details about the implementation will be given in later sections.

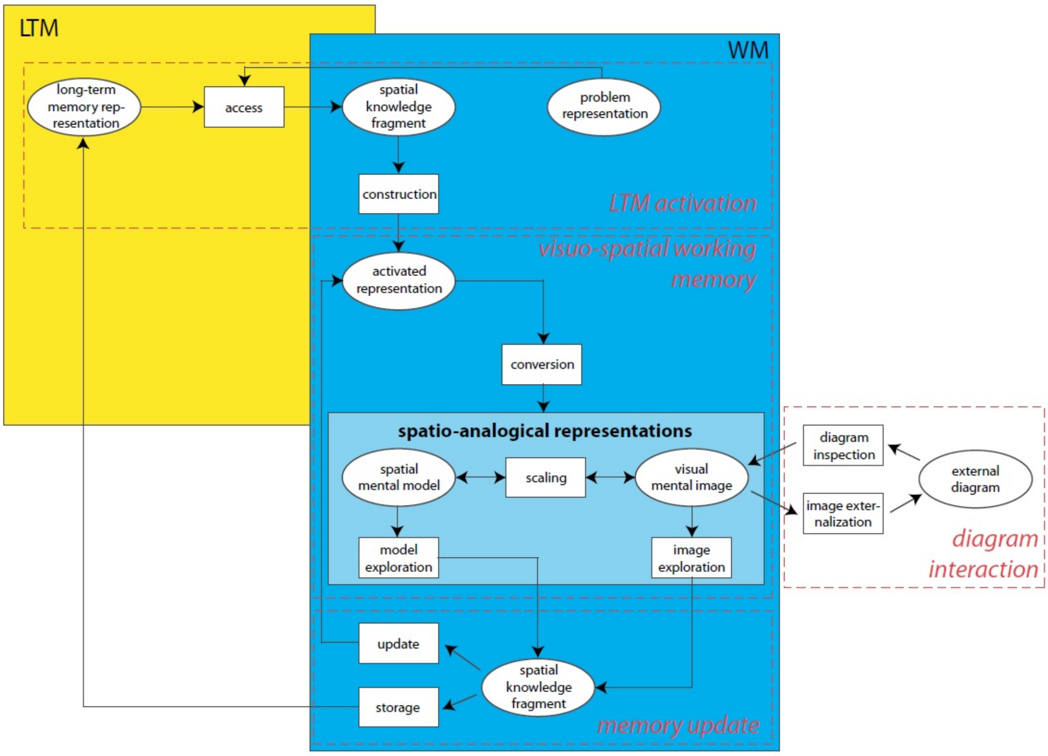

Figure 8: Visualization of Casimir and its components: long term memory (LTM), working memory (WM) and diagram interaction. [Schultheis, Barkowsky (2011)]

3.1.1 Long Term Memory

In the long term memory, Casimir saves already known and learned things. Spatial knowledge is represented as categories of objects such as "city" or "country", concrete objects such as "Paris" or "John", categories of relations such as "distance relation", "direction relation" or "topological relation" and concrete relations such as "far", "south" or "part of". In figure 9 the structure how Casimir stores spatial knowledge in the LTM is visualized.

3.1.2 Working memory

The working memory processes spatial knowledge received from multiple sources, such as memory or from current situations.
Casimir makes a few basic assumptions for spatial knowledge processing. The first assumption says, that spatial information is represented in the form of analogical representations. That means, that knowledge is represented more like an image than a sentence, which is called propositional representation.
In human brains spatial knowledge is neither represented in a fully spatial nor in a fully visual way. It's rather represented in a mixture of these both extremes, therefore the second assumption is, that Casimir should represent mental spatial knowledge as an intermediate of these two extremes. Figure 10 shows multiple ways of how analogical representation of spatial knowledge can be described. Analogical representations become more visual with increasing number of represented relations, increasing number of involved spatial knowledge types, like distances or orientations and increasing specificity as well as increasing exemplarity. Increasing specificity means, that more knowledge about the specific location for a specific object like distance or exact position is known. Increasing exemplarity means, that more knowledge or a more detailed description about the object is available, so the object becomes more unique and can be less described with a prototype or a category.
The third assumption Casimir makes is, that knowledge representation should be kept simple and this will lead to the fact that Casimir's representation of knowledge is scaleable, or at least should be. Scaleability means for Casimir, that only knowledge types (distances, orientations) or entities

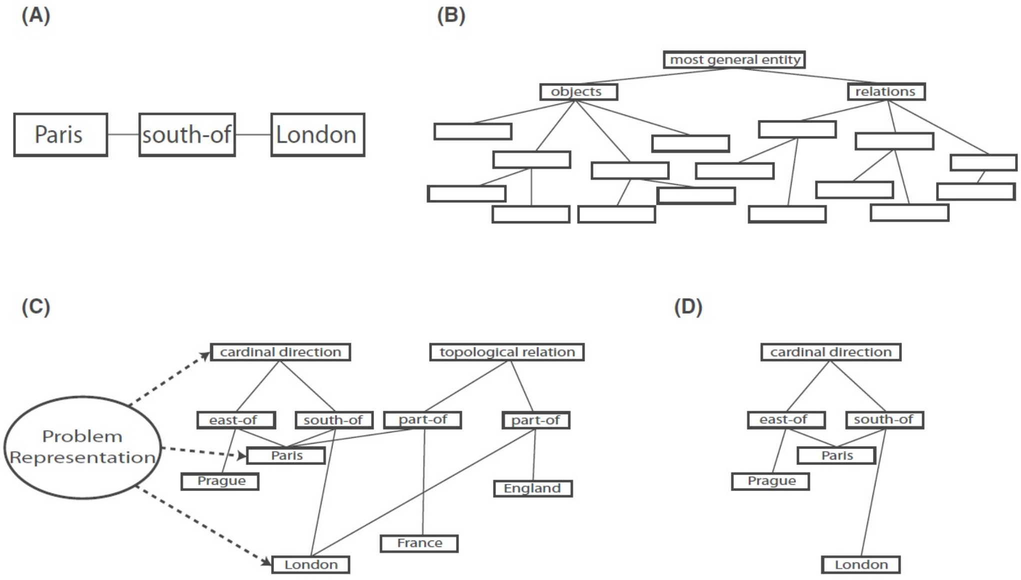

Figure 9: Casimirs representations for objects and relations. (A) represents the fact that Paris is south of London. (B) visualizes a tree structure for objects and relations. (C) describes how a problem transfers to relevant nodes. (D) shows an example of multiple knowledge fragments received from a certain situation. [Schultheis, Barkowsky (2011)]

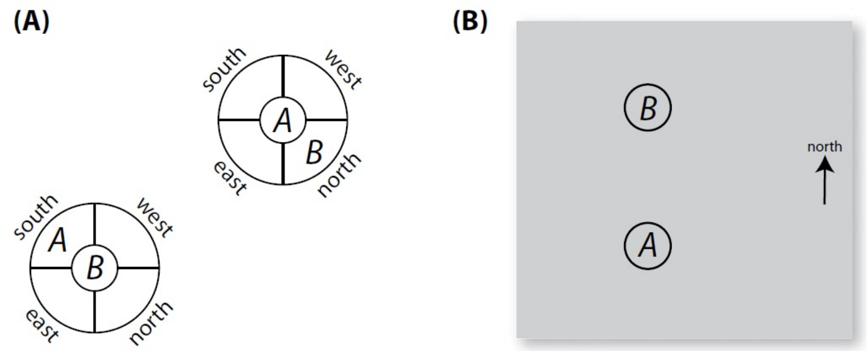

Figure 10: Two analogical representations of the information "A is south of B". (A) represents that fact as a spatial mental image, (B) as a visual mental image. [Schultheis, Barkowsky (2011)]

(north, south) will not be added, before they are needed in order to represent a specific problem or situation.
The propositions "A is north of B" and "B is west of C" can lead to different mental images, that can describe this situation correctly. This will lead to the assumption, that propositions can lead to different possibilities, how they can be represented. Humans often construct the same model for learned propositions, which is called "preferred mental model".
There are three possibilities how new knowledge arises in the spatio-analogical representation in the working memory of Casimir. First: new spatial information is retrieved by the current environment. Second: While reasoning about a specific proposition, that is already learned, the working memory is able to infer new knowledge, such as A is north of B and B is north of C, so it is able to infer knowledge about where A lies in respect to C. And third: constructing spatio-analogical representations may contain more underlying knowledge about the situation. For example, the knowledge processing of the proposition "London is north of Paris" can lead to inherit knowledge about the distance from London to Paris. This is possible, when a lot of knowledge about the situation already exists and therefore the spatio-analogical representation is already very visual. If the spatio-analogical representation is already very visual the brain is forced to draw the new information about London and Paris into the already existing visual mental image and maybe can

inherit from that, that the distance from Paris to London is around 350 km.

3.1.3 Diagram interaction

The diagram interaction module exits, in order to represent internal representation of Casimir and integrate results of visual process into internal processes of Casimir. This module however is not really important, to understand human spatial knowledge processing, so it will be neglected in this project.

3.1.4 Control

Needless to say the overall architecture of Casimir somehow requires control. But Casimir does not have a component which controls all the components and their interaction between each other. Having a control component won't solve the problem of how to realize the control of the architecture, instead it would lead to a new problem, which is: how to realize the control of the control component [Schultheis, Barkowsky (2011)].
Knowledge processing in the human brain is controlled by multiple areas, which are connected to each other. Casimir wants control to be distributed among the components. The control of the components should be emerged, which means control does arise from the interplay between the components during processing knowledge.

3.2 Implementation of Casimir

As a result of lack of information as well as not prioritising all modules of Casimir equally, the implementation workflow was adjusted to the priorities and information found in other papers. In the next subsections the workflow of how Casimir was implemented will be described and justified.

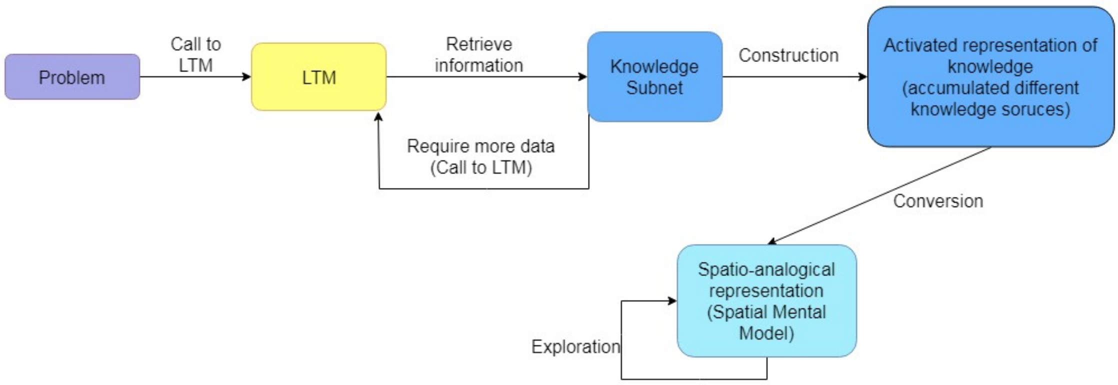

Figure 11: Workflow of the implementation of Casimir.

In figure 11 the workflow of Casimir as it was implemented can be seen. The simulation starts with a problem to be solved by Casimir. This can be for example "London", "Paris" and "Cardinal Directions", which means Casimir should solve that problem by returning the relation which holds between these two cities. As mentioned before, Casimir saves its knowledge as nodes, which are stored in a hierarchical tree form. So the described problem will lead to a search through the nodes saved in Casimirs LTM. The entry points of the example would be the nodes "Cardinal Direction", "London" and "Paris". From these nodes on, the LTM tries to find a connected subnet of knowledge to return to Casimirs working memory. If the knowledge subnet does not hold enough information to solve the problem, the retrieved information will be used to search again through the LTM in order to get more information.
After receiving enough information as a knowledge subnet from the overall knowledge, stored in the LTM, Casimir will parse that knowledge subnet to the working memory, where spatial mental models will be created. Each knowledge fragment such as "London is north of Paris" will be used to get added in an existing spatial mental model, or if there is no suitable one, is is used to create a new one.
After adding all knowledge fragments contained in the knowledge subnet returned from the LTM, Casimir will explore the spatial mental models in order to infer new information. This can be

achieved in different ways. One way is already accomplished while converting the subnet to spatial mental models as for each fragment an opposite fragment is created. If known that "London is north of Paris", than the opposite fact "Paris is south of London" is also already known by Casimir [Schultheis, Barkowsky (2011)]. Another way to infer new knowledge, is to find out which relation exits between two objects, that are placed in the same spatial mental model.
A detailed description about the implementation details will be given in the following subsections.

3.2.1 Implementation of Casimirs Long Term Memory

Casimirs long term memory is a main part of the implementation. The storage of knowledge fragments as well as the activation spreading while retrieving knowledge will be handled there.
The storage of a knowledge fragment for example: "London is north of Paris" is handled pretty simple. Casimir saves the relation and the objects as nodes in its LTM. Casimir knows that "north" is a child of "cardinal direction" and that London and Paris are city objects.
After inserting the knowledge fragments "Paris is in France", "London is in England", "Paris is south of London" and "Prague is east of Paris" the knowledge stored in the LTM is the same as described in figure 12.

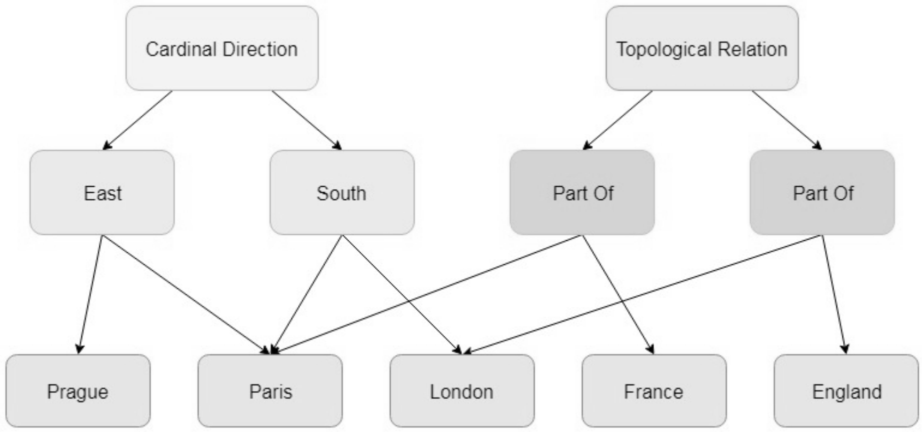

Figure 12: Casimirs representation of stored knowledge in its long term memory. Four knowledge fragments are stored: "Prague is east of Paris", "Paris is south of London", "Paris is in France" and "London is in England", based on the example in the paper, written by Schultheis & Barkowsky (2011). [Schultheis, Barkowsky (2011)]

Receiving a knowledge subnet from the LTM is the most complex part of the simulation. If Casimir needs to solve a problem, it will parse the problem into a context array. The context array describes the problem and contains the entries "cardinal direction", "London" and "Paris, if we want to know the cardinal relation which holds between London and Paris.
When the LTM receives a call the activation of the nodes, stored in the LTM will be calculated in order to find out which nodes can be received. Although it is written by Schultheis & Barkowsky (2011), that the activation value for each node should be calculated, but they did not specify how this should be done. Therefore the information, how the activation spreading as well as the calculation of the activation value could be implemented has been taken from Schultheis, Barkowsky & Bertel (2006), Schultheis, Lile & Barkowsky (2007) as well as from Anderson, Bothell, Byrne, Douglass, Lebiere & Qin (2004). In the Casimir implementation, the activation value of a node consists of three different kind of activation: spread activation, base activation and noise according to the paper written by Anderson, Bothell, Byrne, Douglass, Lebiere & Qin (2004) [Schultheis, Barkowsky, Bertel (2006)].
The spread activation of a node is calculated, while spreading the initial activation from the entry points of the LTM, which are defined by the context array, through all the nodes in the LTM. The initial activation value can be chosen freely, as there is no best default value [Schultheis, Lile, Barkowsky (2007)].
From the initial activated node the value is spread to its connected nodes. The activation value the connected nodes receives is a fraction of the activation value of the nodes, where the activation came from. This fraction of activation is then divided by the amount of children this node has. If

the activation value that a child node would receive is higher than the activation spreading threshold, then the child node will receive that activation value and will spread this activation further.
Also the parameters for the activation calculation of the nodes in the LTM, were not given in the paper of Schultheis & Barkowsky (2011). According to that, the default values of the parameters used for that calculation were taken from Schultheis, Lile & Barkowsky (2007). The chosen default values were 0.6 for the fraction of activation, and 0.01667 for the spreading activation threshold [Schultheis, Lile, Barkowsky (2007)]. Another approach to calculate the spreading activation threshold is to calculate it dynamically for each call to the LTM described by Schultheis, Barkowsky, Bertel (2006). This is done, by calculating the $S_{context} * 10^{-4}$, where $S_{context}$ stands for the amount of nodes in the context array for which a call is made to the LTM [Schultheis, Barkowsky, Bertel (2006)].
After activation spreading has stopped, the base activation of each node in the LTM will be calculated [Anderson, Bothell, Byrne, Douglass, Lebiere, Qin (2004)]. If and how the base activation of a node should be calculated is not described in the paper about Casimir from Schultheis & Barkowsky (2011). Due to the fact, that in all other papers, in which the activation spreading and activation value calculating process in the long term memory is described precisely, also the calculation of the base activation of a node is described, it was decided to calculate the base activation in this simulation as well.
The implementation of the base activation calculation is based on the paper, written by Anderson, Bothell, Byrne, Douglass, Lebiere & Qin (2004) [Anderson, Bothell, Byrne, Douglass, Lebiere, Qin (2004)]. The base activation is calculated by $B = ln(\sum_{i=1}^{n} t_i^{-d})$, where t_i is the time passed by since the i-th usage of a node. The decay factor d is by default 0.5 [Anderson, Bothell, Byrne, Douglass, Lebiere, Qin (2004)]. An usage of an node means, that the node was part of a subnet, that was restored from the LTM or the node was part of a knowledge fragment that was saved in the LTM.
This equation can be mathematically approximated [Petrov, A.A (2006)], but in this simulation for the amount of premises and calls to the LTM the original formula can be used and does not need to be approximated.
The retrieval workflow can be calculated in a even more complex way, by adding the components latency retrieval or probability of retrieval to the equation [Petrov, A.A (2006)]. Latency retrieval describes, that a node can not immediately be retrieved from the LTM and processed. Latency retrieval calculates the time, that is needed until a node is fully restored and can be used. Probability of retrieval adds another random attribute to the retrieval processes, which says if a node can be restored or not. These both aspects weren't implemented as they aren't needed for the experiments, that were carried out. In addition to that, not in all sources found, about the LTM retrieval, these aspects were described.
The noise as third part to calculate the activation value is calculated as a logistic distribution [Anderson, Bothell, Byrne, Douglass, Lebiere, Qin (2004)]. The sum of spread activation, base activation and noise is the activation value of a node.
Whether a node can be retrieved or not is determined by the node's activation. If it is higher than the average activation value of all nodes in the LTM the node can be retrieved [Schultheis, Barkowsky, Bertel (2006)].
After calculating the nodes, which can be retrieved, Casimir is looking for the most activated coherent subnet in its LTM, which is determined by dividing the sum of the activation values of the nodes in the subnet by the amount of nodes in the subnet. The most activated knowledge subnet will be returned to working memory as a response of the LTM retrieval call.
In order to reconstruct the example described in the paper of Schultheis & Barkowsky (2011), that also can be seen in figure 9 (c), the simulation parameter needed to be adjusted. The base activation value needed to be set to 0.86 and the initial activation value to 1.8 in order to receive the correct subnet as described in the example.
If the returned knowledge subnet doesn't contain enough information to solve the problem, Casimir is able to make multiple calls to the LTM in order to recall all knowledge, which is necessary to solve the given task [Schultheis, Barkowsky (2011)]. In the workflow in figure 8 there is no hint how multiple calls to the LTM should be realized. The implementation of multiple calls to the LTM was realized, by creating a new context array, with the already received nodes in the last state. This new context array will be used to make a new call to LTM to receive more knowledge. This is done until all necessary nodes are retrieved or a maximum amount of calls to the LTM has been made, which can be defined as a parameter for the simulation.

3.2.2 Implementation of Casimirs Working Memory

Knowledge fragments, that become part of the working memory of Casimir are used to create mental images. Mental images can be spatial images or visual images. There are many different approaches that are trying to explain how the human working memory works. In Casimir however, the working memory should try to visualize the mental images as a mixture between spatial and visual image.
Normally the more details are known about a certain situation the more visual, rather than spatial, the image would be in the human mind. So mental images should be treated as a hybrid model of spatial and visual models [Bertel, Barkowsky, Engel, Freska (2006)]. Whenever knowledge is processed in the working memory, each knowledge fragment will be used in order to create a mental model. In order to not contradict with the computationally efficy, the human brain is working with, the knowledge processing would try to not represent the same situation in different mental models [Schultheis, Bertel, Barkowsky, Seifert (2007)]. Casimir would create a mental image about the situation in a hybrid way, between the two approaches. The mental image would become more visual as more specific data or details are known about the specific situation.
Casimir is handling the creation of spatial mental model similar to the one in the paper of Schultheis, Bertel, Barkowsky & Seifert (2007) [Schultheis, Bertel, Barkowsky, Seifert (2007)]. In this paper a table is defined, that describes, where humans would place objects based on propositions and their relation to each other. The table also describes where to place objects, which are part of different types of relations, such as distance and cardinal relations.
In this implementation just the spatial mental model will be created. To implementation of the visual image, would be too complicated and until now there is not a lot of research available, that would be able to explain how to construct that kind of images.
Casimir will create spatial mental model based on the knowledge it has received to the LTM. For one situation such as "London is north of Paris" it will create two models. One will be "London is north of Paris" and the second one will be its opposite and inferred proposition "Paris is south of London". For each knowledge fragment, which one by one will be added to the mental representation, Casimir will try to add the knowledge fragment to an existing spatial model or if there is no suitable one, create a new one. For example, if two knowledge fragments just as "London is north of Paris" and "Prague is east of Paris" will be received from the LTM and processed in the WM, the resulting spatial mental module is visualized by figure 13.

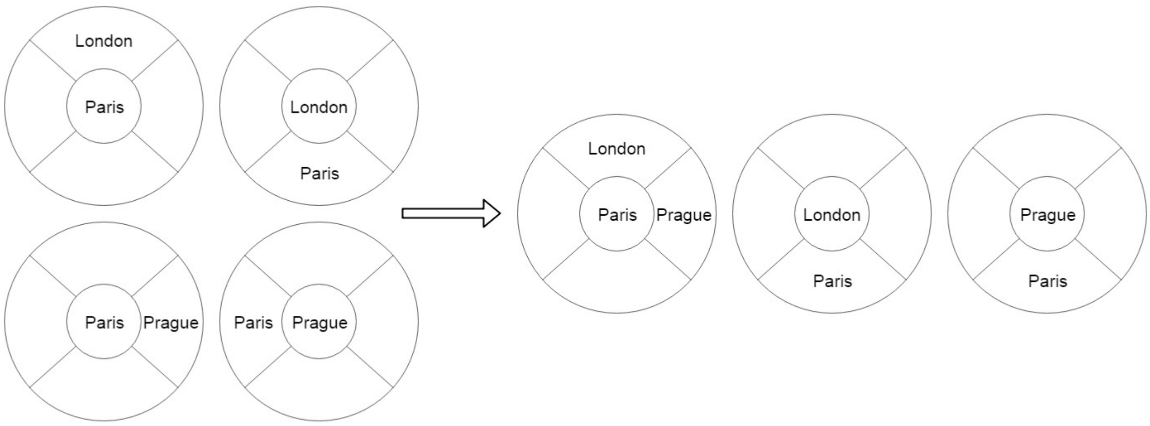

Figure 13: Spatial mental image construction in Casimir Working Memory. The fragment "London is north of Paris" and "Prague is east of Paris" and their resulting opposites are attempted to be combined. From the resulting spatial mental models the relation between the two cities can be inferred.

In the case of the knowledge fragments "A is southwest of B" and "B is northeast of C", Casimir will create the spatial mental model, as visualized in figure 14. For this case, the paper by Ragni & Becker (2010) would predict, that the relation between A and C is "A is west of C", whereas the spatial mental image representation of Casimir as visualized in figure 14 wouldn't [Ragni, Becker (2010)]. The inspection process of the mental model can be lead to more explicit knowledge about a situation, which isn't explicit already stored in the LTM [Sima, Schultheis, Barkowsky (2013)]. In this simulation, as the visual mental image of Casimir wasn't implemented, the inspection process

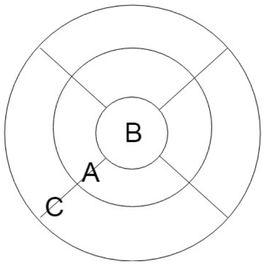

Figure 14: Representation of the created spatial mental image for the knowledge fragments "A is southwest of B" and "B is northeast of C" in Casimirs working memory.

wasn't explicit implemented in a certain step. The inspection process was more or less part of the simulation of the experiments made by Ragni & Friemann. For each task of the experiment Casimir creates a spatial mental model. For each of this spatial mental model implicit knowledge need to be filtered out. The question is, which relations Casimir would predict for the different cases and objects?

3.3 Simulation results

The experiment 1, which was also simulated for LISAs mental array module was also simulated by the Casimir.
Therefore again the two premises of the form "A is north of B" and "B is north of C" were told to Casimir, which stores that knowledge in its LTM. Afterwards it was asked for the relation, that hold between two objects A and C. In order to make that experiment useful, the parameters of that simulation were set so that the total knowledge, that was stored in the LTM was able to be retrieved (in that case the two knowledge fragments given by the task). These knowledge fragments were then used by Casimir to create spatial mental models.

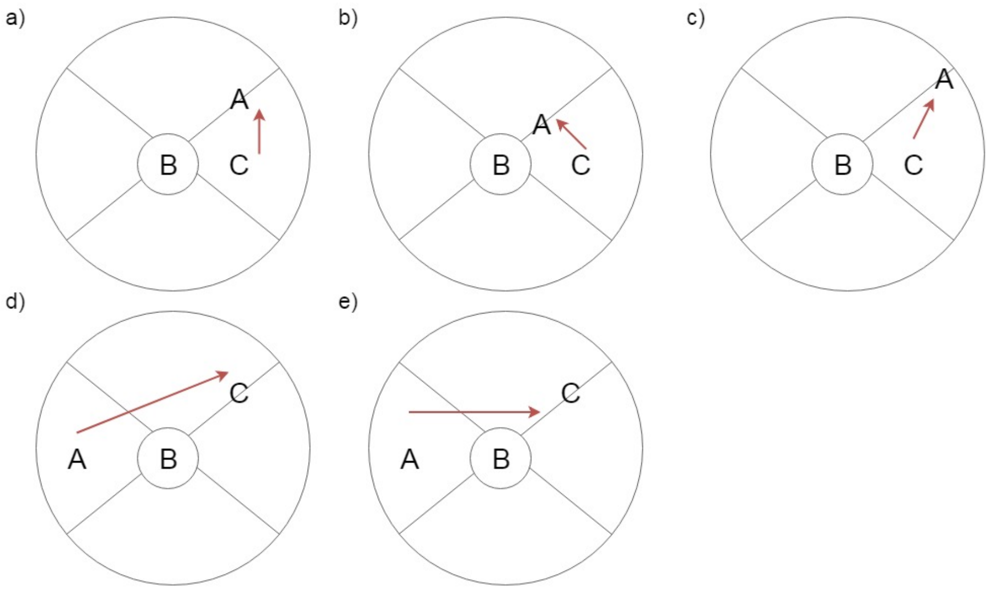

Figure 15: Different possibilities of how humans can place objects and see objects in a spatial mental image. (a) A is north of C. (b) A is northwest of C. (c) A is northeast of C. (d) C is northeast of A. (e) C is east of A.

As seen in figure 15 there are multiple ways how human could place the object A on the northeast axis in the spatial mental image. For the example d) and e) in figure 15 human could tend to say C is north east of A or C is east of A, which would result in the theory that human tend to prefer main cardinal directions [Schultheis, Bertel, Barkowsky (2009)]. But how to find out which relation holds between A and C in these models? In the simulation, which was done for the experiment 1, multiple models were described and compared to each other. The simulation results and the description of the models, are given in the following figure and table:

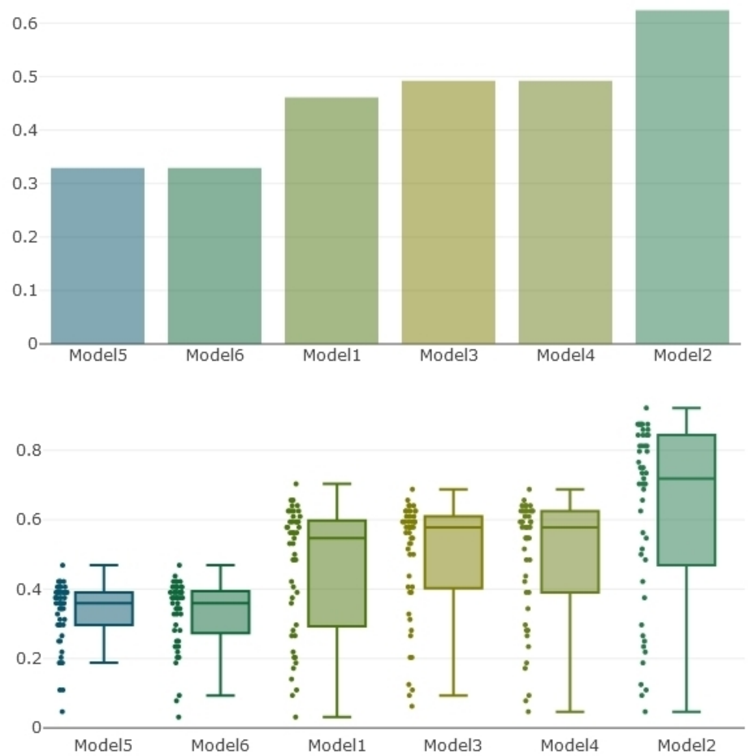

Figure 16: Results of the Casimir Simulation for Experiment 1

	Description
Model 1	Prefer perfect triangles and prefers main cardinal directions
Model 2	Prefer perfect triangle and does not prefer main cardinal directions
Model 3	Prefer dull triangles (place object close to the border) and does not prefer main cardinal directions
Model 4	Prefer sharp triangles (place object close to the middle) and does not prefer main cardinal directions
Model 5	Prefer dull triangles (place object close to the border) and prefers main cardinal directions
Model 6	Prefer sharp triangles (place object close to the middle) and prefers main cardinal directions

Table 4: Models, compared in the Casimir Simulation for Experiment 1

3.4 Casimir Discussion

While implementing Casimir as a cognitive model a lot of questions came up. As explained in the previous sections about the implementation, a lot of details were missing in the paper of Schultheis & Barkowsky (2011) in order to be able to implement Casimir correctly. Therefore the implementation of the retrieval process from the long term memory is based on a lot of different papers. Therefore in the final version of the Casimir simulation, it is possible to choose a lot of parameters, which influence the retrieval process.
Another problem that came up was what happens when the LTM contains many relations of the same type? This will lead to the problem, that if Casimir should solve a task, which asks about what cardinal relation exists between two cities, each of the relations, which is from the type

"cardinal-relation" will just receive a little bit of activation. This happens due to the fact that the spread activation is divided by the amount of children each nodes has. In order to get rid of this problem, the possibility to spread the full activation the each relation of type is implemented.
Due to the fact, that in the paper of Schultheis & Barkowsky (2011), it is not specified what happens, if a relation can't be fully restored. This can happen if the activation value of the relation node is above the average activation, but one of its children's activation value is below average. This problem was solved, by implementing the possibility to decide whether Casimir should be able to just retrieve complete retrievable knowledge fragments or also incomplete ones.
The biggest problem for Casimir was similar as for LISA, how to infer knowledge from a spatial mental model. As described in figure 15 humans see multiple possibilities how to place objects in their own spatial mental model. This question should be tried to be answered by more research. In order to find out which is the most suitable model, the experiment, created by Ragni & Friemann was simulated by Casimir for all different possibilities.
The experiment, which was simulated by Casimir, won't verify Casimirs ability to describe long term memory retrieval. This happens because all knowledge fragments available in its LTM are assumed to be fully retrieved by Casimir. This leads to the open question: would it be useful and possible to verify Casimirs ability to describe humans long term memory retrieval process.
Another open question that couldn't be solved in this project and maybe can improve Casimir is: how to implement the creation of visual images. This question will provide a good starting point for further research.

4 Conclusion

Comparing LISA and Casimir with regards to their ability to describe human spatial knowledge processing is a very complex task. First of all, both approaches are very different from each other. The basic structure on which these models are built on, can't be more different. When propositions in LISA are described in a tree like structure with objects, predicates and semantic units, in Casimir relations and objects are represented as nodes.
Because of its structure LISA is able to know properties of objects, which are represented in LISAs structure as semantic units. LISA tries to find analogies and by mapping the new learned situation to an old already learned situation, LISA tries to infer new knowledge. Casimir on the contrary tries to create mental images and from the created images infer new knowledge.
The experiments both systems were tested for don't fully verify their ability of spatial knowledge processing. An important part about these models is that they describe how humans retrieve knowledge from their LTM, which isn't tested by the experiments.
If one compares the results of both models, which resulted from the evaluation of the experiments, one does not see any big differences. This is because, when evaluating both models, the question arises which relation exists between two objects in the spatial mental array form LISA as well in the spatial mental image, created by Casimir?
In conclusion both of the models have their advantages and disadvantages. LISA is able to describe objects more in detail, because of its structure and their underlying semantic units. But the core point of LISA lies in her ability to find analogies in different situations and uses them to infer new knowledge.
Casimir in contrast is able to infer new knowledge from the spatial mental model it has created. However there a few open points that should be mentioned.
First of all further research should try to answer the questions of: how are humans building visual mental images and how could an implementation of this process look like. Another question waiting for an answer is: which relation do humans see holding between two objects in a spatial mental model or in a spatial mental array.
Another verification of Casimir as a cognitive model, would be designing an experiment that tests Casimirs ability to describe humans long term memory retrieval process.
Finally it can be said that human cognitive abilities are pretty hard to model and to implement, so there is still a lot of research to be done until we finally can understand the underlying structure and processes of the human brain.

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