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A production system for the serial recall of object-locations in graphical layout structures

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Abstract

This paper presents a production system within the ACT-R theory of cognition for the serial recall of object-locations in a graphical layout structure. Concepts of noise and the encoding of object-locations in local allocentric reference systems have been integrated into the visual module for this purpose. The intrinsic reference axis of the local reference systems automatically result from the previously attended objects. The production system describes the process of encoding and rehearsal of object-locations at the stage of the presentation as well at the answer-stage. The model encodes environmental features of the object-locations by object-to-object spatial relations. The production system reproduces the main effects in an experiment which was carried out with 30 subjects.

Introduction

Ehret (2002) and Anderson et al. (2004) describe production systems that reproduce learning curves for the location of information on a display. In these examples the underlying mechanism for learning locations is the same as for the learning of facts. After some practice the location of specific objects like menu buttons can be retrieved without a time consuming random visual search and encoding of labels. In ACT-R the location of a visual object is represented in absolute screen coordinates. Furthermore there is no noise integrated into the visual module. Therefore the location of an object is learned independent of its position on the screen and its position within an object-configuration. But there is evidence that the kind of how objects are displayed has implications on object-location memory. One experiment of Travanti & Lind (2001) investigated object location memory in hierarchical information structures across different instances of 2D and 3D perspective displays. The results of their tests show, that the 3D display improves performance in the spatial memory task they designed. But beside the perspective view also the structure of the object-configuration was different in the 2D and the 3D display. Cockburn (2004) repeated the experiments where he displayed the object-configuration of the 3D display in 2D. He found, that if displayed in 2D the 3D object-configuration improved performance on object-location memory. In both studies the memory task was to associate alphanumerical letters to the object-locations. Therefore Cockburn suspected that the vertical orientation of Travanti & Lind's 2D display made the formation of effective letter mnemonics more difficult than the horizontal 3D layout, because words and word combinations normally run horizontally left to right. By analyzing these studies we came to the conclusion that one major factor had not been considered - the factor of the object-to-object spatial relations (the structure of the graphical layout respectively). Therefore we performed own experiments in which the structure of the object-configuration were varied. Furthermore, to avoid subjects to create letter mnemonics in our experiments the task was to memorize sequences of highlighted objects (Winkelholz et al. 2004). The object-configurations investigated are shown in figure 4a. In each encoding retrieval trial, the subject was presented one structure. After an acoustical signal the computer started to highlight objects of one randomly created sequence. Only one object of the sequence was highlighted at once. The sequences were five (*A* structures) and six (*B* and *C* structures) items long. The end of a sequence was indicated by a second acoustical signal. Each object of a sequence was highlighted for 2 seconds. Subjects were instructed to repeat the highlighted objects in correct order, by clicking them with the mouse. As a measure of performance the number of correct repeated sequences was chosen. The displayed dependencies of the overall performance on the object-configurations (figure 4b) show two things. First, that a horizontal orientation of a structure improves the performance in the memorizing task compared to a vertical orientation (A_1 compared to A_3). Second, performance increases the more distinct object-to-object relations are within a structure. E.g. in the matrix structures B_1 and B_2 the object-to-object relations covers the whole plane, whereas in the linear structure B_3 object-to-object relations are only in one dimension. Since there is no difference in the performance between structure B_1 and B_2 this effect can not result from spatial vicinity. As well suggests the effect in the performance between C_1 and C_2 that noisy object-to-object relations are needed to model this effect. While object-locations are represented in absolute screen-coordinates this effect can not be modeled on the level of production rules within ACT-R and some extensions to the visual module are needed. One promising approach in this direction was suggested by Johnson et al. (2003) who extended ACT-R to automatically encode object-to-object relations between the previously and currently attended objects. Based on this approach we extended the visual module not only to encode the spatial relation of previously and currently attended object, but also to use the two previously attended objects to form a local reference axis according to which the location of the current attended object is encoded. Furthermore, we integrated a noise model into the visual module, extended the mechanism of visual indexing and integrated some kind of competitive chunking mechanism in the equation for the activation.

Visual Module Extensions/Restrictions

Reference systems

The location of an object can only be identified within a frame of reference. In experimental psychology it is well accepted to divide the frames of references into two categories: An egocentric reference system, which specifies the location of an object with respect to the observer and an environmental (allocentric) reference system, which specifies the location of an object with respect to elements and features of the environment. As mentioned above the visual module of ACT-R encodes object-locations in the reference-system of the screen, which is equivalent creating all spatial object relations to one edge of the screen. However, according to Mou & McNamara (2002) humans also use reference systems concerning the intrinsic axis of the object configuration. E.g. two salient objects create an axis that is used to specify the location of other objects. The most natural way to integrate this into the concept of attention of the visual module is to consider the last two attended objects as an axis of reference. This is an extension to the proposal of Johnson et al. (2003) considering only the previously attended object in creating object-to-object relations, which means that only the distance is represented in a pure environmental reference system and the angles in an egocentric reference system. However, creating object-location memory chunks in this "semi-allocentric" reference system is less effort to the visual module because it only needs to keep track of two objects, whereas in the case of the pure allocentric reference system three objects are needed. Therefore in some situations the production system might be forced to use spatial memory chunks in the semi-allocentric system. We considered in the visual module all three different reference systems, which are summarized in Figure 1.

The introduction of object-relations based on three objects is important for three reasons: First, it fits well with the concept of intrinsic axis in the object configuration as reported by Mou & McNamara (2002). Second the concept of angles is essential to most cognitive operations in geometric tasks. Third, it is the simplest percept for spatial memory chunks that allows reconstructing object locations, also if the whole configuration is rotated.

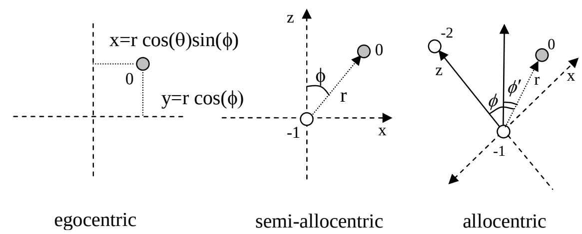

Figure 1: Three different reference systems. The objects are attended in the order (p_{-2}, p_{-1}, p_0)

Noise

The variances in recalled object-locations require the memory chunks to be noisy. To integrate noise into the memory chunks the first question is how object-locations in different reference systems are represented in memory. Huttenlocher et al. (1991) showed among other things, that the distribution of recalled locations supports the assumption that subjects imagine object-locations on a plane relative to a center in polar coordinates. We generalized this to use spherical coordinates in respect to an extension of the visual module in three dimensions. This assumption has also some interesting implications on the representation of locations on a screen. Spherical coordinates are a system of curvilinear coordinates that are natural for describing positions on a sphere or spheroid. Generally θ is defined to be the azimuthal angle in the xy-plane from the x-axis, ϕ to be the polar angle from the z-axis and r to be distance (radius) from a point to the origin. In the case of the allocentric reference system this means, that if the three points p_{-2}, p_{-1}, p_0 were attended and p_0 has to be represented in a local allocentric reference system, the point p_{-1} defines the origin, the polar axis is given by (p_{-1}, p_{-2}), and the local spherical y-axis points orthogonal into the screen. For the semi-allocentric reference system, again p_{-1} is the origin, but the polar axis is parallel to the vertical axis of the screen and the x-axis is parallel to its horizontal axis. In the case of the egocentric reference system the viewpoint of the subject is the origin. In the typical scenario of a user interacting with symbols on the screen the differences in the angles and distances between symbols represented in the egocentric system are very small compared to the differences if represented in an allocentric, or semi-allocentric reference system. Therefore, if the same magnitude of noise is assumed in all reference systems, memory chunks represented in the egocentric reference system would be extremely more inaccurate compared to object-locations represented in the other two reference systems and therefore can nearly be neglected. The next question is, if θ,ϕ, and r should be considered as single, independent memory chunks. Because it is impossible to imagine a distance without a direction and an angle without corresponding lines, it is reasonable to combine distance and angular as one percept in one memory chunk. Because of this argument, also in the case of the actual allocentric reference system the egocentric orientation of the reference system should be stored into the memory chunk. This does not imply that the angular or the different dimensions of one chunk can not be separated later. In spatial reasoning often two angles have to be compared. But this can be handled as commands to the visual module. Then also timing issues can be considered for example for the mental rotation of an actual allocentric reference system. In principle the spatial information of the semi-allocentric reference system is now also present in the chunk of an actual allocentric reference system. This might suggest discarding memory chunks of the semi-allocentric reference system. But as mentioned above, creating object-location memory chunks in this semi-allocentric reference system is less effort to the visual module and therefore in some situations needful. Finally a spatial location is represented by $D(r,\theta,\phi,\theta',\phi',e_{rs})$, where r,θ,ϕ are the spherical coordinates as described above, e_{rs} indicates in which reference system r,θ,ϕ have to be interpreted, and ϕ',θ' are a additional attributes for the actual allocentric reference system and holds additionally the polar and azimuth angle in the semi-allocentric reference system. The values of the spherical coordinates in the memory chunk are interpreted as random numbers distributed according to a truncated logistic distribution $f(x,x_0,\sigma_x)$, with to each dimension corresponding standard deviations $(\sigma_r(\phi',r),\sigma_\theta,\sigma_\phi)$. The scalar value in the slot of the memory chunk indicates the maximum x_0 of the distribution. The noise in the r-dimension is biased by a factor according to if the distance to be estimated is vertically or horizontally oriented. Furthermore, the noise σ_r is relative to r. As the final noise in the r-dimension we use:

$$\sigma_r(\phi',r) = (f_{\sigma_r} + (1-f_{\sigma_r})\cos^2(\phi'))\sigma_r r \qquad (1)$$

Every time a location is to be encoded, it is decided if the perceived values for the location correspond to an already existing memory chunk. The posterior probability $P_{Di}=P(D_i|F_x)$ that the location of a feature F_x belongs to a memory chunk M_i and the probability P_0 that no appropriate memory chunk already exists, are given by

$$P_{D_i} = \frac{P(F_x \mid D_i)}{V^{-1} + \sum_i P(F_x \mid D_i)}, \; P_0 = \frac{V^{-1}}{V^{-1} + \sum_i P(F_x \mid D_i)} \qquad (2)$$

The parameter V^{-1} describes the weight of a noisy background and

$$P(F_i(r,\theta,\phi,\theta',\phi') \mid D(r_x,\theta_x,\phi_x,\theta'_x,\phi'_x)) = \qquad (3)$$
$$f(r,r_x,\sigma_r)\, f(\theta,\theta_x,\sigma_\theta)\, f(\phi,\phi_x,\sigma_\phi)\, f(\theta',\theta'_x,\sigma_\theta)\, f(\phi',\phi'_x,\sigma_\phi)$$

On the other hand, if an object-location is requested based on a memory chunk $D(r,\theta,\phi,\theta',\phi',e_{rs})$, the values are set to random values according to (3). After the noise has been added to the location request, it is decided if the values are latched on possible features in the display. Therefore, the object-locations of all features $F_i(r_i,\theta_i,\phi_i,\theta'_i,\phi'_i)$ in question are calculated in the current local reference system corresponding to the reference system in the request. The probability P_{Fi}, that the location request is caught by feature F_i and the probability P_0 that it is not, are given similarly to (2) by

$$P_{F_i} = \frac{P(x \mid F_i)}{V^{-1} + \sum_i P(x \mid F_i)}, \quad P_0 = \frac{V^{-1}}{V^{-1} + \sum_i P(x \mid F_i)}. \qquad (4)$$

These equations express the posterior probability $P_{Fi}=P(F_i|x)$ that if a noisy location x from the memory is given the location results from the feature F_i. The likelihood probability functions $P(x|F_i)$ are the truncated logistic distribution according to if the feature F_i would have been the stimulus and are similar to (3). The process of encoding and reconstruction of a location into a random number in memory is illustrated in figure 2.

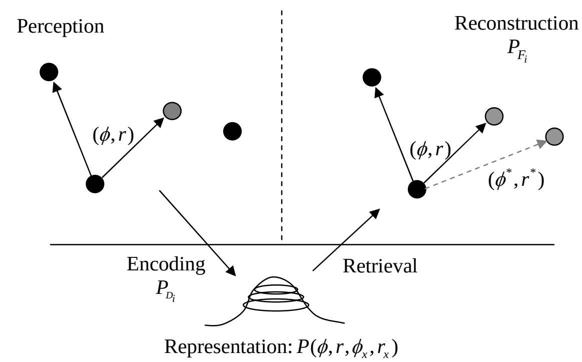

Figure 2: Perception, representation and reconstruction of a location

This noise model has two interesting properties. First, because the truncated logistic distribution is asymmetric, the expected report of an object-location is biased away from the reference axis. This is the same effect as reported at categorical boundaries. Second, for object-locations on a flat screen the values of θ,θ' are discrete $\theta,\theta'=(\pi/2,0,-\pi/2)$ and encode whether the object-location in question is on the left side, on the right side, or aligned, when facing into the direction of the reference axis. This is consistence with the assumption to interpret the reference axis as a categorical boundary, where θ encodes the category.

Visual Indexing

It is evident that subjects browsing a graphical layout structure encode environmental characteristics of object-locations, e.g. if an object is located on the border of a matrix. To encode such environmental features the cognitive system needs to attend objects nearby. The crucial point is that after some objects in the environment have been attended, attention needs to return to the object in question. If this return would depend on noisy spatial memory chunks, the strategy to encode environmental features might be highly counterproductive. At this point the concept of visual indexing, or FINST - FINger INSTantiation, (Pylyshyn, 1989) is needed. According to this theory the cognitive system has “access to places in the visual field at which some visual features are located, without assuming an explicit encoding of the location within some coordinate system, nor an encoding of the feature type". Experiments suggest that the number of FINSTs in the visual system is limited to the number 4 to 5. In the visual module of ACT-R the concept of FINST is used to decide if an object has already been attended. Whenever an object is attended, a FINST is created. Because the number of simultaneously existing FINST is limited, any time a new visual object is attended the oldest FINST is removed to create a new FINST for the currently attended object. To implement environmental scan patterns, FINST need to provide additionally to the information that an object has already been attended also information for accessing its location without, or at least minimal noise. In the visual module interface described in the next section this has been accomplished by determining a visual index through the sequential position in the chain of attended locations. This index can be used in visual module commands to return (or avoid to return) attention to a particular location in the chain of attended locations.

The visual module interface

Figure 3 shows the visual module interface, with the slots that have been added, and the slots whose meaning have been extended.

Perception:

```
=visual-location>
  vsl-e     symbol ;egocentric
  vsl-a     symbol ;allocentric
  vsl-sa    symbol ;semi-allocentric
  kind      [text,..,empty]
  index1  [nil, t]
  index2  [nil, t]
  index3  [nil, t]
  index4  [nil, t]
  index5  [nil, t]
```

Action:

```
+visual-location>
  vsl-r symbol
  vsl-theta symbol
  vsl-phi symbol
  vsl-mtheta symbol
  vsl-mphi symbol
  ignore-sa [t nil]
  vsl-ix [back1,..,back5]
  attended [not1,..,not5,noti1,..noti5]
```

Figure 3: Modified visual module interface.

For each reference system one slot (*vsl-e*, *vsl-a*, *vsl-sa*) has been added containing a symbolic value of a memory chunk encoding the location in the respective reference system (egocentric, allocentric, semi-allocentric). These symbolic values can be used to request new locations in the visual field. For this purpose the command-slots *vsl-r*, *vsl-phi*, *vsl-mphi*, *vsl-theta*, and *vsl-mtheta* have been added. For each dimension (r, θ, ϕ) there is a slot extracting this dimension from the spatial memory chunk given to this slot. Thus, the dimensions of different spatial memory chunks can be combined to one request. The *ignore-sa* slot ignores the semi-allocentric components of a pure allocentric memory chunk so that it can be applied to a rotated configuration. The angular dimensions can be inverted through the slots *vsl-mphi* and *vsl-mtheta* ($\theta \to \theta > 0 ? \theta - \pi : \theta + \pi$, $\phi \to \arccos(\cos(\phi + \pi))$). This approach enables the visual module to compare the length of two distances or to scan an imagery path backwards. Only spatial memory chunks within the same reference system can be combined. Possible sub-symbolic parameters for timing and if any combination should be disabled or new operations have to be added, need to be investigated in future work. The request for a new location through these slots may prompt the visual module to attend an empty location. This case is indicated by the symbol EMPTY in the kind slot. First, we tried to implement the environmental scan patterns only by using these slots. But it turned out that as long as these requests are noisy operations, it was too risky to loose the actual object-location in question during an environmental scan. The possible gain of information for an object location was culled by this noise. Therefore we introduced the slots *index1*,..,*index5*, and *vsl-ix* to have precise access to indexed locations. The slots *indexN* indicate whether the currently attended location has already been attended at position *N* (counted backwards) in the chain of attended locations. By using the descriptive identifiers *backN* on the slot *vsl-ix* a particular location in the chain of already attended locations can be re-attended. The possible descriptive identifiers on the attended slot have been extended to *notN* and *notiN*. The *notN* identifier prevents the visual-module to attend a location that has already been attended within the last *N* attended locations. The *notiN* identifier prevents the visual module to attend a location that has been attended exact at position *N* in the chain of attended locations. Only with this access to indexed locations it is possible to "weave" a reliable network of object-to-object spatial relations.

Competitive Chunking

A subject learning object-locations in a graphical structure becomes familiar with the structure after some time. This means he recognizes environmental features faster and is therefore able to link environmental features more efficient to object-locations. The concept of familiarity within a symbolic architecture of cognition has already been discussed by Schreiber-Evert & Anderson (1990). They developed the theory of competitive chunking (CC), which assumes that memory chunks are supported by subchunks. For example subjects are able to learn sequences of letters more efficient, if the sequence contains well known words or syllables. This is because the memory chunk for the sequence can be compressed by replacing elements of the sequence by references to subchunks having a high activation and can therefore be retrieved reliably and fast from memory. The concept of CC as described by Schreiber & Anderson is not part of the current version of ACT-R. However, we suspect that such a concept is needed, to describe the effect of becoming familiar with a configuration of objects. One way to manage subchunks within ACT-R is to couple them tightly to their parent chunks by their symbolic values in specific slots. This method does not result in an effect considered as CC, because it doesn't allow accessing associated subchunks by free association. In many situations only one of possible several subchunks associated with the parent chunk needs to be retrieved, but by this approach the slots need to be retrieved consecutively. Therefore, a more promising approach is to couple chunks only by symbolic tags they share. This way e.g. an arbitrary number of environmental features can be associated with one object-location, and can be retrieved competitively. The problem is that subchunks that have been learned in context of different parent chunks carry the same information but differ in the tag shared with its parent chunks. In the sense of CC they should be supported because of their common patterns. To study this effect in the learning of environmental features we extended ACT-R's activation equation for memory chunks by the following term:

$$C_i = c_{cc} \sum_{m=1}^{n_s} \sum_{n \neq 1}^{n_s} \sum_{k}^{N} I_{mni} K_{mnik} \left[B_k + \frac{\ln(1 + e^{-c_d B_k})}{c_d} \right] \qquad (5)$$

The index k runs through the chunks of the same kind, the index m and n through the slots of the chunk type. The parameter K_{mnik} compares the similarity of the slot values and can be expressed by the similarity parameters of the partial matching term:

$$K_{mnik} = \begin{cases} e^{M_{m_i m_k}} e^{M_{n_i n_k}}, \text{ if } e^{M_{m_i m_k}} e^{M_{n_i m_k}} > c_\tau \\ 0 \text{ ,otherwise} \end{cases} \qquad (6)$$

The partial matching parameter $M_{m_i m_k}$ we interpret as the log probability $ln(P(v_{mi}=v_{mk}))$ that the value in slot m of chunk D_i results from the same source as the value of slot m of chunk D_k. This is in accordance with the default choice of $M_{ij}=0$ if the slot values are equal.. Hence K_{mnik} is the probability that both values are equal. To limit the contributions, K_{mnik} is cut by a threshold c_τ. So roughly speaking the sum of the K_{mnik} over the slot pairs is a measure of how many equal slot values chunk i and k share. If only K_{mnik} is used as a factor for the competitive chunking, also slots contribute, which values are equal over all chunks, which means that they do not carry any information. Therefore we introduced the factor I_{mni}, that estimates how much normalized information the knowledge of the value $V_m=v_{mi}$ in slot m of memory chunk D_i contains about the values V_n in slot n of the other chunks.

$$\mathrm{I}_{mni} = 1 - \frac{H(V_n \mid V_m = v_{mi})}{H(V_n)} \qquad (7)$$

I_{mni} is zero if v_{mi} contains no information about V_n and 1 if V_m is fully determined by the knowledge of v_{mi}. If the slots only contained clearly distinguishable symbolic values, the entropies in (7) could be calculated by the frequencies. But in the case of spatial memory chunks the similarities have to be taken into account.

$$H(V_n) = -\frac{1}{N} \sum_{k}^{N} \ln \frac{\sum_{k'}^{N} e^{M_{n_k n_{k'}}}}{N} \qquad (8)$$

$$H(V_n \mid V_{mi} = v_{mi}) = -\frac{1}{\sum_{k'}^{N} e^{M_{m_i m_{k'}}}} \sum_{k}^{N} e^{M_{m_i m_k}} \ln \frac{\sum_{k'}^{N} e^{M_{n_k n_{k'}}} e^{M_{m_i m_{k'}}}}{\sum_{k'}^{N} e^{M_{m_i m_{k'}}}} \qquad (9)$$

In the limit of clearly distinguishable slot values the equations (8) and (9) are identical to a formula estimating the probabilities of the entropies for the information by the frequencies of the slot values. Further, the contribution of each chunk is weighted by a factor according to its basis activation B_k with a lower bound to zero for and approximating B_k for large activations.

Due to the additional term (5) in the activation equation virtual subchunks emerge through the clustering of attribute values, which support their container chunks.

Simulation

We used the extended visual module to model human performance in a task for the serial recall of object locations in graphical layout structures briefly reviewed in the introduction.

Production rules

The production system we developed describes the encoding and retrieval stage of the memorizing task. During the encoding of the sequentially presented object-locations the previously highlighted objects up to the current location are rehearsed. During the rehearsal, environmental features of the object locations are encoded or it is checked if one to the object-location retrieved environmental feature matches the environment of the current object. If the environment does not match, the reference system is restored through the visual indexes, and a new guess is made excluding the denied object-location. The environmental features are encoded in competing chunks with a symbolic tag to the corresponding object-location and spatial relations to objects in its neighborhood. To check an environmental feature is time consuming, because it has to be retrieved from memory. Therefore, the production rules for checking or encoding the environment compete. The answer stage is equal to the rehearsal stage, except that environmental features are not encoded anymore and are only checked. Overall the production system contains 142 rules. This unexpected high number of rules results from the time pressure set on the task. At any possible stage the model needs to check if a new card is highlighted, which leads to a lot of exceptions needed to be handled.

Most ACT-R parameters were left at their defaults, and subsymbolic computation was enabled. Further, retrieval threshold (:rt 0.0), latency factor (:lf 0.35) and maximum difference (:md -100). The variance $\sigma_{(\theta,\phi)}$ of the noise for the angular dimension was set to *0.06* radians and to *0.08* for the *r*-dimension. This is smaller than the standard deviation reported by Huttenlocher et al. (1991), but in their experiments no reference point was displayed, hence noise might be larger because of an uncertain reference location. The skewing factor f_r in eq. (1) of the noise in the *r*-dimension was chosen to be *0.8*. The parameter for the background noise was set to *V=2.e3*. The competitive chunking parameters were set to $c_c=0.7$, $c_d=1.0$ and $c_\tau=0.8$. For all simulations and graphical structures the same parameters and production rules were used.

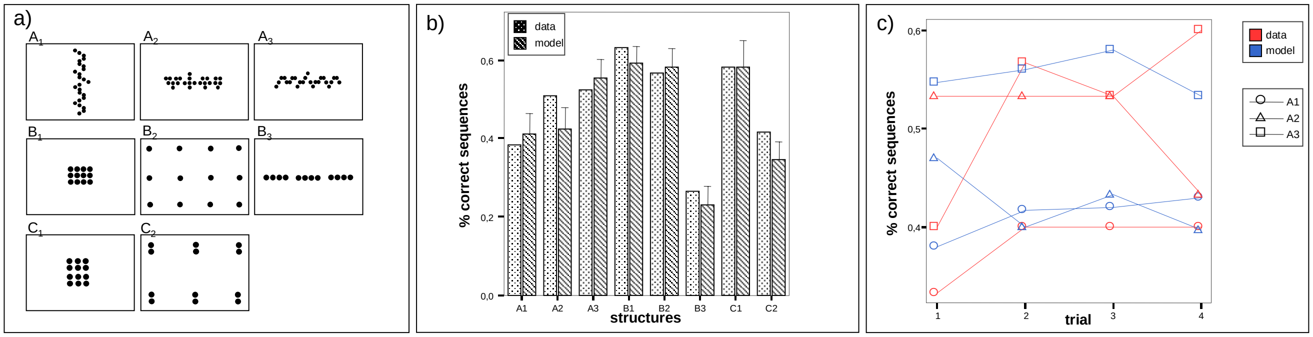

Figure 4: a) graphical layout structures used in the experiments. b) overall performance, c) learning curves

Results

The results are shown in figure 4. The output of the simulation model adequately fits the data (R^2=0.83). However, the simulation exhibits no learning curve. The competitive chunking mechanism worked as intended. The traces of the model reveal that in the first trial only the environmental feature of the first object-location gets enough activation to be retrieved, at the last trial mostly the environmental features of the first four object-locations are retrieved. But to get some kind of saturation from existing chunks in the competitive chunking equation, we let the model first learn sequences in random object-configuration. After this saturation the other structures seems not to be distinct enough to change the effects in the competitive chunking equations. The learning curves in the experimental data are not significant, so they should not be over-interpreted. The model underestimates the performance of the subjects in the symmetrical tree structure A_2. This may indicate that the visual system takes advantage of symmetries in an object-configuration that are not captured by the model yet. This could be done by more sophisticated scan patterns or the saturation in the competitive chunking should have been done by training the model on more regular structures.

Conclusions and Future Work

This paper described extensions to the visual-module of the ACT-R/PM theory that allows developing very detailed models for the visual working memory. The concepts were derived from well known effects in experimental psychology. In conclusion the modeling gave us a deep insight into the mechanisms and bottlenecks of encoding object-locations. One challenge in modeling the memorizing task was the limited number of FINSTs. The number of FINST limits the complexity of environmental features that can be encoded. This is interesting with respect to visual working memory in three dimensions. In three dimensions encoding of an object-location in a real allocentric local reference system needs at least three object locations to define a reference plane. This reduces the number of free FINST in an encoding task. This might explain why spatial reasoning in three dimensions is for most people more difficult than spatial reasoning in two dimensions. In future work we will extend the concepts described in this paper to three dimensions. Furthermore, we currently investigate how the occurrence of noisy scalar values in attributes of memory chunks should be considered in the equation for learning of association strength and base level learning. Furthermore, spatial reasoning tasks might be modeled in future work.

References

Anderson, J. R., Bothell, D., Byrne, M. D., Douglass, S., Lebiere, C., & Qin, Y . (2004). An integrated theory of the mind. *Psychological Review 111*, (4). 1036-1060.

Ehret, B. D. (2002). Learning where to look: Location learning in graphical user interfaces. CHI Letters, 4(1), 211–218.

Cockburn A (2004). Revisiting 2D vs 3D Implications on Spatial Memory. *Proceedings of the Fifth Australasian User Interface Conference* (AUIC2004). Dunedin, New Zealand. January 2004, pages 25-32.

Huttenlocher J., Hedges L. V., Duncan S. (1991): Categories and Particulars: Prototype Effects in Estimating Spatial Location. Psychological Review, Vol. 98, No. 3, 352-376, 1991.

Johnoson, T.; Hongbin W.; Zhang J. (2003): Modeling the use of multiple frames of reference for object location memory. *Proceedings of 10th Annual ACT-R Workshop.*

Mou, W., & McNamara, T. P. (2002). Intrinsic frames of reference in spatial memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 28, 162-170.

Pylyshyn, Z. W. (1989): The role of location indexes in spatial perception: A sketch of the FINST spatial-index model. *Cognition*, 1989, 32, 65-97.

Servan-Schreiber E., & Anderson J.R. (1990) Chunking as a mechanism of implicit learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 16, 592-608.

Travanti , M. & Lind M. (2001). 2D vs 3D, Implications on Spatial Memory. In proceedings of the IEEE Symposium on Information Visualization 2001.

Winkelholz, C.; Schlick, S.; Brütting, M. (2004).The effect of structure on object-location memory. *Proceedings of the Twenty-Sixth Annual Conference of the Cognitive Science Society*. Mahweh, NJ: Lawrence Erlbaum Associates.