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Computer Science/Department of Interactive Systems Report CS-R8829 December

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The 'Structural Memory'; a Network Model for Human Perception of Serial Objects

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In this article we present the 'Structural Memory', a network model for human perception of serial objects, such as series. Our theoretical assumptions originate from the Structural Information Theory (SIT) (Buffart & Leeuwenberg, 1983; Leeuwenberg, 1969), a theory concerning the perceptible structures in an object and concerning the human preference for one of these structures. A symbolic notation of such a perceptible structure in an object is called a *representation.* For a given maximum number of symbols we can generate all representations automaticly. Based upon this procedure we define *G(eneration)-relations* between the representations. Furthermore, we define *S(tructure)-relations* based upon the structures described by the representations. The representations and the relations can be seen as respectively the nodes and the links in a *network.* This network is the basis for the 'Structural Memory'. Therefore, we assign an *activation value* to each representation in the network, expressing the strength of the preference for the described structure at a certain moment. By means of a *process model* we are able to make predictions for the strength of the preference for a perceptible structure in an object. The process is only based upon the network structure, because of a found relation between the preference measure, used in SIT, for a perceptible structure in an object and the number of G- and S-relations of the corresponding representation in the network. Shown is that with two of these process models already some experiments (van Leeuwen & Buffart, 1988; van Leeuwen et al., 1988) can be simulated.

1980 Math. Subject Classification: 69K16, 69K69, 92A25.
Keywords & Phrases: human perception of serial objects, Structural Information Theory, representations, network model, spreading of activation, distributed memory, simulation.
Notes: This research was supported by the Psychon Foundation, which is aided by the Netherlands Organization for the Advancement of Pure Research (ZWO). The work was done at the University of Nijmegen, Department of Experimental Psychology, P.O. Box 9104, 6500 HE Nijmegen, The Netherlands. This article will appear in Psychological Research.

Report CS-R8829
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1. Introduction.

In a recently published article "Sequence Influence on the Organization of Meaningless Serial Stimuli: Economy After All" (van Leeuwen et al., 1988) a number of experiments are reported concerning the influence of earlier perceived objects on the perception of a serial object. By excluding other explanations these authors showed that the found influence can only be explained by a network model. In this article we will elaborate on this network model, and show how it can be used to simulate some of the mentioned experiments.

From a mathematical point of view a network is a connected, directed graph: a set of nodes and links, in which the nodes are connected by directed links. By assigning a time-dependent variable to each node in the network, it is possible to define a dynamic process in which for some nodes the value of their variable is dependent on external information (object or *input*) and for some nodes this value is readable (behaviour or *output*). A network with a dynamic process is called a *network model.* When the current value of the variable, called *activation value*, also depends on earlier values, a network model can be seen as a memory model. A network model can also be seen as a model for human perception if each object is identified or classified in a human way by a characteristic set of activation values.

Recently, the use of network models has expanded enormously in cognitive-psychological research at perception and retrieval of objects (McClelland & Rumelhart, 1981; Roediger & Neely, 1982; Rumelhart & McClelland, 1986). These authors usually represent the nodes in a network as object-features and the links are derived from the meaning of the nodes. This means that the structure of the network depends on the set of represented objects, which has, however, the disadvantage that the network must be extended with new nodes and links when an object with not yet represented features is appended to the set of represented objects. Considering the fact that the number of possible object-features is unlimited, this implies that the structure of such a network can not be derived theoretically. The network model we present in this article can be distinguished from the afore mentioned approach, because the structure of our network is derived from object-independent theoretical assumptions. The object-independency is realized at a functional level (Marr, 1982), because the definition of the nodes and links in our network is based upon all psychological allowable representations of serial objects (Buffart, 1987; Buffart & Leeuwenberg, 1983). As suggested by van Leeuwen (1988) prospects for a model which is object-independent at a functional level are better than for models which realize their independency at a computational or even implementational level (Anderson et al., 1977; Kohonen et al., 1981; Kohonen, 1984). In the networks of these authors the nodes have no specific meaning and all links are derived from the same principle. The consequence is that, in contrast with the object-dependent networks, there are no psychological constraints on the structure of this network. Because these network models can, opposite to what is assumed for humans (Geissler & Puffe, 1983), learn every relation between objects with equal ease, they have not much relevance as models for human learning behaviour.

In the next paragraph we present the theoretical assumptions for the 'Structural Memory'. The network is introduced in the third paragraph, while the network model is described in the fourth paragraph. Some experiments (van Leeuwen & Buffart, 1988; van Leeuwen et al., 1988) are simulated with the network model, which is reported in the fifth paragraph. In the sixth and last paragraph we discuss the results and conclusions.

2. Theoretical assumptions.

Percepting an object is seen by Restle (1970), in accordance with the principles of the Gestalt psychology (Koffka, 1935), as structuring the object, or in other words as detecting or finding relations between elements of the object. In this article we restrict ourselves to objects with unambiguous defined elements in a certain order, the so-called *serial objects*. Examples of these objects are pitch series, like 'do re mi do' with 'do', 're' and 'mi' as elements, or symbol series, like '+ – o – +' with '+', '–' and 'o' as elements, but also line drawings whose graph contains a eulerian path (i.e. a drawing which can be made without taking the pencil from the paper), like the drawing '/\/\' with '/' and '\' as elements.

2.1. Patterns and representations.

A symbolic notation of a serial object is called a *pattern*. This is a series of symbols, usually letters from the alphabet, in which each symbol refers to an element in the object, with preservation of the order. Identical elements are represented by the same symbol, while different symbols are represented by different symbols. A symbolic notation of the serial object '/\/\' is for example the pattern '*ABABAB*' or '*FGFGFG*'. In this symbolic notation the symbols are abstract, meaningless, they only reflect which elements are identical, or in other words which identity-relations exist between elements in the object.

All existing identity-relations between elements are usually not simultaneously detected when the object is perceived. So the perceived structure in the object does not have to be complete. Suppose for example that someone in perceiving the serial object '/\/\', detects that the first element is equal to the third and that the fourth element is equal to the sixth. These perceived identity-relations can also be described by a symbolic notation, in the above case for instance by '*pqprsr*' or '*vwvxyx*'. In this notation only the perceived identical elements are represented by the same symbol. Such a symbolic notation of the perceived structure in a serial object, is called a *representation*.

Summarizing, a symbolic notation of all existing identity-relations in a serial object is called a pattern, while a symbolic notation of only the perceived identity-relations in a serial object is called a representation. For a better distinction we will always use the capital letters '*A*' until '*Z*' for the symbols in the patterns and the letters '*a*' until '*z*' for the symbols in the representations.

2.2. Perceptible structures.

The difference between patterns and representations is of importance because we assume that it is not always possible to perceive all existing identity-relations in a serial object simultaneously. By that we mean that not every combination of identity-relations between elements can form a perceptible structure in a serial object. The constraints that are thus imposed on the allowable representations, originate from the Structural Information Theory (SIT) (Buffart & Leeuwenberg, 1983; Leeuwenberg, 1969). This theory states that humans can only perceive those structures in a serial object which comply with one of the following syntax rules:

Iteration — All elements are identical.
Examples of allowable representations are '*k*', '*pp*' or '*xxxxxx*'.

Symmetry — The last elements are the mirror image of the first elements.
Examples of allowable representations are '*klk*', '*pqqp*' or '*xyzyx*'.

Alternation — Elements are alternated with other elements.
Examples of allowable representations are '*klkm*', '*psqsrs*' or '*xyxyxyxy*'.

Furthermore, humans are also able to perceive structures that comply with combinations of these rules. This is stated in the so-called *substitution principle*, which allows a perceptible structure to be described by a representation in which symbols are substituted by representations. An example of this is the representation '*xyxxyxxyx*', which can be seen as '(*xyx*)(*xyx*)(*xyx*)', i.e. an iteration '*ppp*' in which each symbol '*p*' is substituted by the symmetry '*xyx*'.

The representations that are allowable according to the Structural Information Theory, can also be derived from a general theory (Buffart, 1986) concerning representations of objects. This theory assumes that the perceptible structures in an object are always hierarchically. Applied to the serial objects it appears that through this *hierarchy-constraint* precisely the same representations are allowable (Buffart, 1987), with only a few exceptions.[1] From now on a perceptible structure is a structure that complies with one of the syntax rules or the substitution principle, or with the hierarchy-constraint.

2.3. Preference.

Usually several structures can be perceived in a serial object, which means that there are also several representations that describe a perceptible structure in the object. The Structural Information Theory states that humans have a preference to perceive a specific structure, and that this preference can be predicted by the *economy principle* (Hatfield & Epstein, 1985). This principle states that the representation which describes a perceptible structure in the object most economically, reflects the preferred perceived structure. In order to measure the economy of a representation, Leeuwenberg and his colleagues used the so-called I-load, which is defined as the number of different symbols in the symbolic notation plus every iteration and symmetry.[2] For example the representation '*xxxyz*' has an I-load of four, namely three different symbols and the iteration '*xxx*'. Preference for the representation with the lowest I-load is predicted.

Predicting the preference by using the I-load, does not take the influence of the earlier perceived objects into account. However, experiments (van Leeuwen & Buffart, 1988; van Leeuwen et al., 1988) have clearly shown that there is such a sequence influence on the preference. With the network model presented in this article, the 'Structural Memory', it will be possible to predict the preference for a perceptible structure in accordance with the economy principle, but in a manner which is not independent of the influence of the earlier perceived objects. The network we use as the basis for this model will be introduced in next paragraph.

3. Network.

The nodes in the network correspond with all allowable representations. For a given maximum length – the maximum number of symbols – of the representations, a computer program can generate automaticly all these representations. During the generation there are also relations

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[1] There are a few representations whose structure can be described by the symmetry-rule, like '*xyxyyxyx*', while this structure does not comply with the hierarchy-constraint. Opposite, there are also a few representations, like '*xyxyx*', whose structure complies with the hierarchy-constraint, while it can not be described by the syntax rules or the substitution principle.

[2] This formulation of the definition of the I-load is unsound. Firstly, the original definition of the I-load is formulated in terms of an operator language, in which only the representations that are allowable by the rules of Leeuwenberg are described. The representations that are not allowable by the rules of Leeuwenberg (see note 1), have to be left outside our definition, because it is impossible to formulate a consistent definition of their I-load. Secondly, due to the symbolic notation we use in describing the representations, the given definition for the I-load is in some cases ambiguous. For example, the representation '*xyxy*' can be seen as an alternation with an I-load of three (the three different symbols), but also as '*x*' followed by the symmetry '*yzy*', which gives an I-load of four ('*x*', two different symbols in '*yzy*' and the symmetry). In those cases we define the I-load as the minimum of the possible I-loads.

determined between the representations. The links in the network correspond with these relations.

3.1. Generation of representations.

All allowable representations with a specified maximum length are generated by a recursive procedure. This means that for the generation of a representation with length n one or more representations with no more than length $n-1$ are used. The generation procedure consists of four generation rules, which guarantees that only perceptible structures are described by the generated representations. These rules are:

Iteration For every length a representation with only identical symbols is generated.
Examples are: → '*x*'
→ '*xx*'
→ '*xxxxxx*'

Symmetry The symbols of an already generated representation are followed by the same symbols in opposite order and an optional new symbol in between.
Examples are: '*xy*' → '*xyyx*'
'*xy*' → '*xyzyx*'

Alternation The symbols of two already generated representations, whose length does not differ more than one, are alternated.
Examples are: '*xz*' and '*yy*' → '*xyzy*'
'*xzx*' and '*yy*' → '*xyzyx*'

Substitution One or more symbols of a generated representation are substituted by already generated representations. Identical symbols have to be substituted by the same representations.
Examples are: '*xk*' with k = '*yzy*' → '*xyzy*'
'*pqp*' with p = '*xx*' and q = '*yz*' → '*xxyzxx*'

As one might have notified in the above examples, there are representations which can be generated in several ways. For example, the representation '*xyzy*' is generated by the alternation- and the substitution-rule. This aspect is the major difference with the generation procedure of Mellink & Buffart (1987). These authors designed a procedure in which each representation can be generated in one way only. The importance of this difference will become clear when we discuss the relations between the representations.

3.2. Relations between representations.

Buffart (1987) showed that there are relations between representations. In this article we distinguish two types of relations, the *G(eneration)-relations* based upon the generation rules and the *S(tructure)-relations* based upon the structures described by the representations. Both types of relations are automaticly determined during the generation of the representations.

When a generation rule in generating the representation r_1 makes use of the representation r_2, we define that r_1 has a G-relation with r_2. The examples of the generation rules show that, for instance, the representation '*xyzy*' has a G-relation with the representations '*xy*', '*xx*' and '*xyx*'. So is '*xyzy*' generated by the alternation-rule using '*xz*' (or '*xy*') and '*yy*' (or '*xx*') and by the substitution-rule using '*xk*' (or '*xy*') and '*yzy*' (or '*xyx*'). Note that for a G-relation of r_1 with r_2 it does not make any difference on how many ways r_1 can be generated using r_2. Because a representation has G-relations with all representations that are used for its generation, the unique

generation procedure of Mellink & Buffart (1987) is not capable to determine all possible G-relations.

When the structure described by the representation r_1 includes implicitly a structure described by the representation r_2, we define that r_1 has an S-relation with r_2. In other words, r_1 has an S-relation with r_2 if all identity-relations described by r_2 are also described by r_1. An example of this is the representation '*xyyy*' which has an S-relation with '*xyzz*'. The representation '*xyzz*' describes namely only that the third element is equal to the fourth. This identity-relation is also described by '*xyyy*', but this representation describes furthermore that the second element is equal to the third and the fourth element. So the structure described by the representation '*xyyy*' includes implicitly the structure described by the representation '*xyzz*'. We assume that a representation has always an S-relation with itself.

3.3. Network structure.

The representations and their mutual relations can be seen as respectively the nodes and the links in a network. Figure 1 shows this network for representations with a maximum of four symbols; the links are also shown in Table 1 for clearity. The network has through the generation procedure a characteristic network structure, because for every representation it is exactly determined how many and which G- and S-relations it has. It is important to note that the G- and S-relations of a representation are independent of the size of the network, i.e. independent of the maximum length of the representations in the network.

representation	'p'	'pp'	'pq'	'ppp'	'ppq'	'pqp'	'pqq'	'pqr'	'pppp'	'pppq'	'ppqq'	'ppqr'	'pqpq'	'pqpr'	'pqqp'	'pqqq'	'pqqr'	'pqrp'	'pqrq'	'pqrr'	'pqrs'	G	S	L	I
'p'	S	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0	1	1	1
'pp'	–	S	S	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	0	2	2	2
'pq'	G	–	S	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	1	1	2	2
'ppp'	–	–	–	S	S	S	S	S	–	–	–	–	–	–	–	–	–	–	–	–	–	0	5	3	2
'ppq'	–	G	G	–	S	–	–	S	–	–	–	–	–	–	–	–	–	–	–	–	–	2	2	3	3
'pqp'	G	G	–	–	–	S	–	S	–	–	–	–	–	–	–	–	–	–	–	–	–	2	2	3	3
'pqq'	–	G	G	–	–	–	S	S	–	–	–	–	–	–	–	–	–	–	–	–	–	2	2	3	3
'pqr'	G	–	G	–	–	–	–	S	–	–	–	–	–	–	–	–	–	–	–	–	–	2	1	3	3
'pppp'	–	–	–	–	–	–	–	–	S	S	S	S	S	S	S	S	S	S	S	S	S	0	13	4	2
'pppq'	–	–	G	G	–	–	–	–	–	S	–	S	–	S	–	–	S	–	–	–	S	2	5	4	3
'ppqq'	–	G	G	–	G	–	G	–	–	–	S	S	–	–	–	–	–	–	–	S	S	4	4	4	3
'ppqr'	–	G	G	–	G	–	–	G	–	–	–	S	–	–	–	–	–	–	–	–	S	4	2	4	4
'pqpq'	–	G	G	–	–	–	–	–	–	–	–	–	S	S	–	–	–	–	S	–	S	2	4	4	3
'pqpr'	–	G	G	–	–	G	–	–	–	–	–	–	–	S	–	–	–	–	–	–	S	3	2	4	3
'pqqp'	–	G	G	–	–	G	–	–	–	–	–	–	–	–	S	–	S	S	–	–	S	3	4	4	3
'pqqq'	–	–	G	G	–	–	–	–	–	–	–	–	–	–	–	S	S	–	S	S	S	2	5	4	3
'pqqr'	–	G	G	–	G	–	G	G	–	–	–	–	–	–	–	–	–	S	–	–	S	5	2	4	4
'pqrp'	–	–	G	–	–	G	–	–	–	–	–	–	–	–	–	–	–	–	S	–	S	2	2	4	4
'pqrq'	–	G	G	–	–	G	–	–	–	–	–	–	–	–	–	–	–	–	–	S	S	3	2	4	3
'pqrr'	–	G	G	–	–	–	G	G	–	–	–	–	–	–	–	–	–	–	–	–	S	4	2	4	4
'pqrs'	–	–	G	–	–	–	–	G	–	–	–	–	–	–	–	–	–	–	–	–	S	2	1	4	4

Table 1. For all representations with a maximum of four symbols the mutual G- and S-relations are shown. Furthermore, G, S, L and I are respectively the number of G- and S-relations, the length and the I-load for each representation.

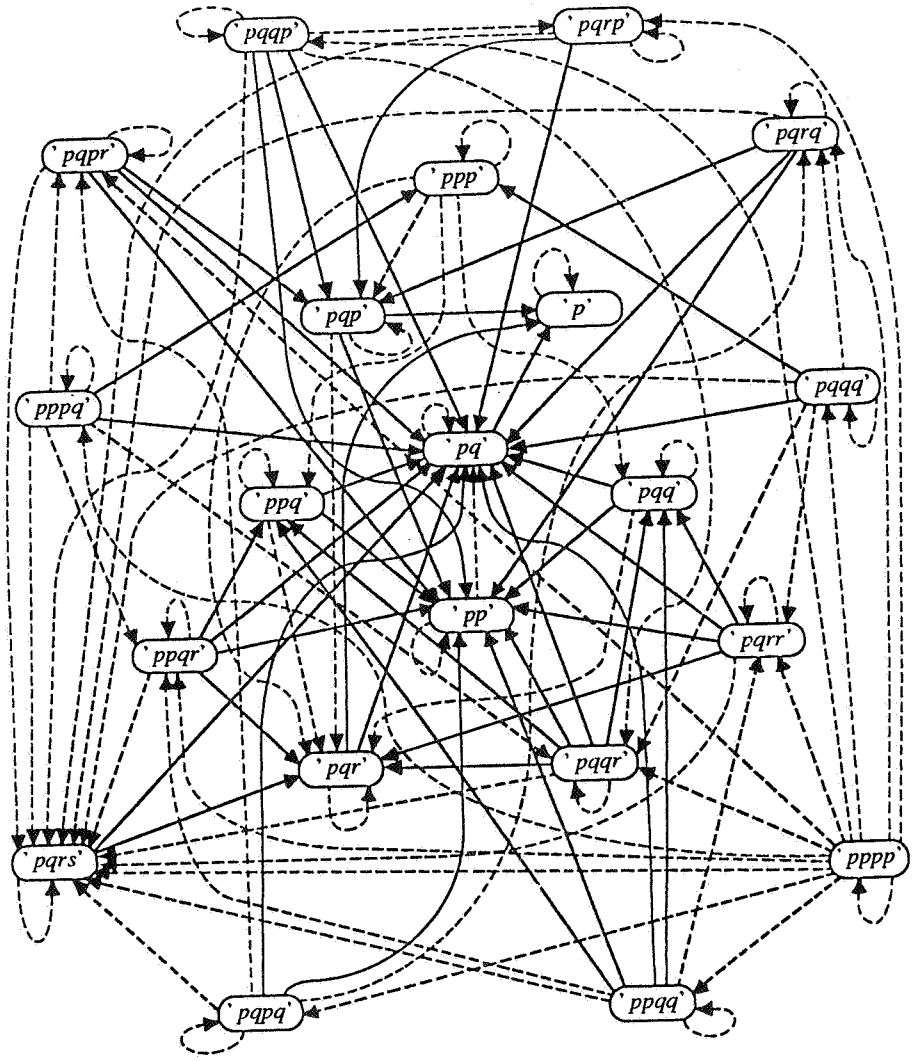

Figure 1. The network for representations with a maximum length of four symbols. The continuous and the dotted lines are respectively the G- and the S-relations.

We would like to find out in what way the network structure is relevant for the prediction of the preference of a subject for a perceptible structure in an object. Because until now SIT has derived the prediction from the economy principle using the static I-load, by stating that the representation with the lowest I-load will be preferred, we will investigate if there is any relation between the I-load of a representation and the number of its G- and S-relations in the network. Because the I-load is usually larger when the length of a representation is longer, the length can also have a role in this relation. To give an idea of the different numbers, Table 1 also shows the number of G- and S-relations, the length and the I-load of all representations with a maximum of four symbols. To investigate if there is a relation we performed a multivariate analysis – UNIX-STAT; regress (see Chapter 4 in Kerlinger & Pedhazur, 1973) –, in which is tried to express the I-load of each representation as a linear combination of the number of its G- and S-relations and its length. This multivariate analysis will give a regression equation – the best linear combination – in plain and standard score form (i.e. with mean 0.0 and standard deviation 1.0). However, only regression equations in standard score form can be compared. The analysis gives

furthermore the variable Mult-R, indicating how good the I-load is expressed by the regression equation.

This multivariate analysis is performed for the networks in which the maximum length of the representations varies between five and nine. The reason for this is that a length shorter than five and longer than ten are theoretically not interesting (Buffart, 1987) and that the network with a maximum length of ten is hard to generate, because of the limited capacity of our PDP-11/44 computer. Table 2 shows the results of the analysis for the different networks. Since the number of S-relations increases faster compared to the number of G-relations when the I-load increases, we also made a multivariate analysis in which is tried to express the I-load as a linear combination of the number of G-relations, the *square root* of the number of S-relations and the length. The results for the different networks are shown in Table 3.

Max	Mult-R	Regression equations in standard score form			Regression equations in plain form				
		w(G')	w(S')	w(L')	w(G)	w(S)	w(L)	c	w(G)/w(S)
5	0.9042	I' = 0.2228 G'	+ -0.3955 S'	+ 0.7153 L'	I = 0.1021 G	+ -0.0683 S	+ 0.7042 L	+ 0.5510	-1.4949
6	0.8773	I' = 0.3934 G'	+ -0.3507 S'	+ 0.5235 L'	I = 0.1365 G	+ -0.0318 S	+ 0.5328 L	+ 0.9751	-4.2952
7	0.8657	I' = 0.4333 G'	+ -0.2982 S'	+ 0.5046 L'	I = 0.1160 G	+ -0.0145 S	+ 0.5401 L	+ 0.9227	-8.0000
8	0.8286	I' = 0.4580 G'	+ -0.3027 S'	+ 0.4532 L'	I = 0.0958 G	+ -0.0079 S	+ 0.5222 L	+ 1.0924	-12.1266
9	0.8015	I' = 0.4843 G'	+ -0.2511 S'	+ 0.4318 L'	I = 0.0796 G	+ -0.0035 S	+ 0.5262 L	+ 1.1352	-22.7429

Table 2. The results of the multivariate analysis in which the I-load is expressed as a linear combination of the number of G- and S-relations and the length for the networks in which the maximum length of the representations is between 5 and 9.

Max	Mult-R	Regression equations in standard score form			Regression equations in plain form				
		w(G')	$w(\sqrt{S'})$	w(L')	w(G)	$w(\sqrt{S})$	w(L)	c	$w(G)/w(\sqrt{S})$
5	0.9145	I' = 0.1870 G'	+ -0.4500 $\sqrt{S'}$	+ 0.7913 L'	I = 0.0857 G	+ -0.4715 $\sqrt{S}$	+ 0.7790 L	+ 0.8911	-0.1818
6	0.9043	I' = 0.3015 G'	+ -0.4675 $\sqrt{S'}$	+ 0.6456 L'	I = 0.1046 G	+ -0.3657 $\sqrt{S}$	+ 0.6570 L	+ 1.1190	-0.2860
7	0.8976	I' = 0.3380 G'	+ -0.4238 $\sqrt{S'}$	+ 0.6134 L'	I = 0.0905 G	+ -0.2616 $\sqrt{S}$	+ 0.6565 L	+ 0.9533	-0.3459
8	0.8859	I' = 0.3306 G'	+ -0.4852 $\sqrt{S'}$	+ 0.5795 L'	I = 0.0692 G	+ -0.2327 $\sqrt{S}$	+ 0.6678 L	+ 0.9425	-0.2974
9	0.8714	I' = 0.3495 G'	+ -0.4676 $\sqrt{S'}$	+ 0.5512 L'	I = 0.0574 G	+ -0.1808 $\sqrt{S}$	+ 0.6717 L	+ 0.8441	-0.3175

Table 3. The results of the multivariate analysis in which the I-load is expressed as a linear combination of the number of G-relations, the square root of the number of S-relations and the length for the networks in which the maximum length of the representations is between 5 and 9.

From the reported results[3] in Table 2 and 3 follow three important conclusions. Firstly, the I-load of a representation can be rather well expressed as a linear combination of the number of G- and S-relations and the length, but even better as a linear combination of the number of G-relations, the square root of the number of S-relations and the length, because the Mult-R is in Table 2 between 0.8015 and 0.9042 and in Table 3 between 0.8714 and 0.9145. This means that there is indeed a relation between the I-load of a representation and the network structure. Secondly, for the regression equations in standard score form it appears that in Table 2 the weight of the number of G-relations is increasing and the weight of the number of S-relations is

[3] The representations for which no I-load is defined (see note 2) are not incorporated in the analysis.

decreasing when the size of the network is increasing. However, in Table 3 the weight of the number of G-relations and the weight of the square root of the number of S-relations is approximately constant in the different networks. This means that using the square root of the number of S-relations, the found relation is independent of the maximum length of the representations in the network. Thirdly, for the regression equations in plain form it appears that the ratio of the weight of the G-relations and the weight of the S-relations is decreasing in Table 2, but remains about constant in Table 3 when the size of the network is increasing. This means that the contribution to the I-load of the absolute number of G-relations and of the square root of the absolute number of S-relations for the I-load is proportionally constant in the different networks. This last conclusion is important for the 'Structural Memory', where in the next paragraph the *absolute* numbers of G- and S-relations will be used as determinants of the preference.

4. 'Structural Memory'.

The 'Structural Memory' is a network model based upon the network defined in the last paragraph. With this network model we want to predict the preference of a perceptible structure in a presented serial object dependent on the earlier presented objects. Therefore, a time-dependent variable is assigned to each node in the network, expressing the strength of the preference for the corresponding representation. In a so-called *process model* is described how the current value, called *activation value*, of such a variable is determined as a function of the current and previous presented objects. Because in this way the network model can be seen as a memory model of the human perception, it is called a 'Memory'.

When there is no influence of the earlier presented objects, the preference of a representation can be predicted by the economy principle, using the I-loads of the representations. Because of the found relation between the I-load and the number of G- and S-relations of a representation in the network, we will use the network structure as the basis in a process model for predicting the preference. With this basis we know that if there is no influence of the earlier presented objects, the prediction will be more or less the same as with the economy principle. Because in this way the determination of the activation values in a process model will be based upon the network structure, the network model is called 'Structural'.

In this paragraph we define two almost similar process models. The *input* for these process models is a pattern, the symbolic notation of the current presented serial object. The *output* at a certain moment is a set of activation values of a number of representations, from which the behaviour of the subject can be derived. The activation values are determined in both process models by a test-procedure and a decay-procedure.

4.1. Test-procedure and decay-procedure.

The test-procedure starts at the moment when a pattern is presented. This procedure tests in parallel all representations against the structure described by the presented pattern. A representation is *confirmed* if its structure fits with the structure described by the pattern, i.e. if all identity-relations described by the representation are also described by the pattern. Opposite, all identity-relations described by the pattern do not have to be described by the representation. The result of this test-procedure is that the activation value of a confirmed node will increase and that the activation value of a non-confirmed node will not change. After the test-procedure the decay-procedure starts automaticly. The result of this procedure is that at the same time the activation value of each node in the network will decrease.

If we assume that activation values are bounded, then we can suppose that each value lies

between 0.0 and 1.0. To assure this, we suppose that each activation value is always a value of the functions $p(x)=1-e^{-x/P}$ or $q(y)=e^{-y/Q}$, with P and Q as parameters. As Figure 2 and 3 show, the values of these functions are always between 0.0 and 1.0 for $x>0.0$ and $y>0.0$. Furthermore, we suppose that 0.5 is the original activation value of all nodes.

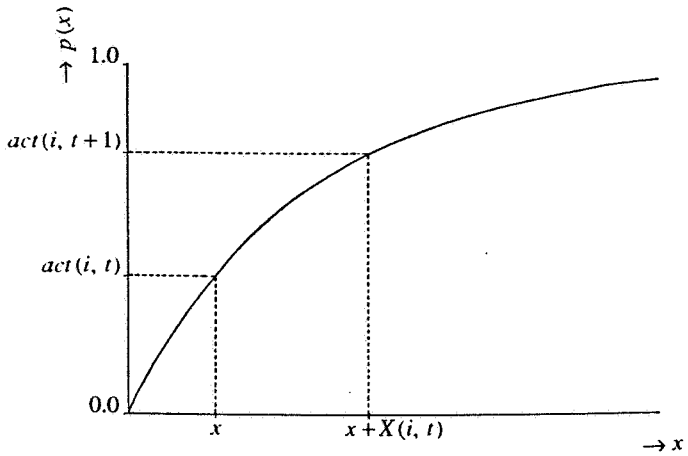

Figure 2. The function $p(x)=1-e^{-x/P}$.

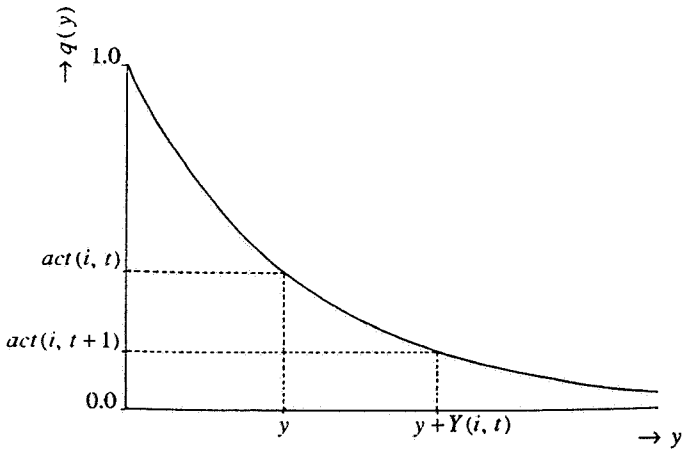

Figure 3. The function $q(y)=e^{-y/Q}$.

The activation value $act(i, t)$ of node i is supposed to be a function value of the function $p(x)$, if i is *confirmed* at time t. As Figure 2 shows, there is always exactly one x with $act(i, t)=p(x)$. The activation value of node i increases as a result of the confirmation, which is expressed as an increase of x with step $X(i, t)$. It appears that, see (1), the new activation value $act(i, t+1)$ depends only on the old value $act(i, t)$, the step $X(i, t)$ and the parameter P.

$$
\begin{aligned}
act(i, t+1) &= p(x+X(i, t)) \qquad (1)\\
&= 1.0-e^{-(x+X(i, t))/P}\\
&= 1.0-e^{-x/P}\times e^{-X(i, t)/P}\\
&= 1.0-(1.0-p(x))\times e^{-X(i, t)/P}\\
&= 1.0-(1.0-act(i, t))\times e^{-X(i, t)/P}
\end{aligned}
$$

In an analogous way the activation value $act(i, t)$ of node i is supposed to be a function value of

the function $q(y)$, if i *decays* at time t. As Figure 3 shows, there is also always exactly one y with $act(i, t)=q(y)$. The decay of the activation value is expressed by an increase of y with step $Y(i, t)$. It appears that, see (2), the new activation value also depends only on the old value $act(i, t)$, the step $Y(i, t)$ and the parameter Q.

$$\begin{aligned} act(i, t+1) &= q(y+Y(i, t)) \\ &= e^{-(y+Y(i, t))/Q} \\ &= e^{-y/Q} \times e^{-Y(i, t)/Q} \\ &= q(y) \times e^{-Y(i, t)/Q} \\ &= act(i, t) \times e^{-Y(i, t)/Q} \end{aligned} \tag{2}$$

Dependent on the choice for $X(i, t)$ and $Y(i, t)$ there are several process models possible. As argued before, we will present here two models in which the choice is based upon the network structure.

4.2. Process model 1.

The analysis of the network structure showed that the I-load can be well expressed as a linear combination of the number of G-relations, the square root of the number of S-relations, and the length of a representation. In the regression equations (see Table 2 and 3) the weight of the G-relations is positive and the weight of the S-relations is negative. Since a representation with a low I-load will usually have a high preference, the corresponding node will usually have a high activation value. This implies that an activation value must increase stronger or decrease weaker when the representation has less G-relations or more S-relations than other representations. An activation value must, in turn, increase weaker or decrease stronger when the representation has more G-relations or less S-relations than other representations.

In this first model we take the step $X(i, t)$ for a confirmed node i, equal to the square root of the number of S-relations of i. This means that, according to the above condition, the activation value will increase stronger if i has more S-relations than other confirmed nodes. For the decay of the activation value of node i, we take the step $Y(i, t)$ equal to the number of G-relations of i. This means that the activation value will decrease stronger if i has more G-relations than other nodes, also according to the above condition. Note that in this model all G- and S-relations of i are counted once, or better formulated, they all have the same weight of 1.0, see (3).

$$\begin{aligned} X(i, t) &= \sqrt{s_i} = \sqrt{\sum_{j=1}^{s_i} 1.0} \\ Y(i, t) &= g_i = \sum_{j=1}^{g_i} 1.0 \end{aligned} \tag{3}$$

with s_i the number of S-relations and g_i the number of G-relations of i.

Since the final strength of an activation value is mainly determined by the ratio of the number of G-relations and the square root of the number of S-relations, the third conclusion from the analysis of the network structure is important here. It stated that the ratio between the weights of the absolute numbers of relations remains constant when the size of the network increases, so that the here formulated process model is independent of the maximum length of the representations.

4.3. Process model 2.

In the second process model the formulas for $X(i, t)$ and $Y(i, t)$, shown in (4), are similar to those in the first model. The difference is that in this model the weight of each relation depends on the activation value of the node connected through that relation. In the first model a relation has a weight of 1.0, but in this model the weight is between 0.5 and 1.5. The step $X(i, t)$ will be larger and the step $Y(i, t)$ will be smaller than in the first model, if the activation value of a node connected with i is higher than 0.5. In this way the activation value of the node i will increase stronger if it is confirmed, and will decrease weaker if it decays, when the connected nodes are high activated. This is opposite to the first process model in which the activation values of the nodes have no influence on each other. Therefore, the second process model is the more realistic one. The first model can be seen as a rough approximation of the behaviour of the second model, and can presumably be applied only in those situations, where the direct influence between representations is not expected to be extremely important.

$$X(i, t) = \sqrt{\sum_{j=1}^{s_i} (0.5 + act(S_i(j), t))} \qquad (4)$$

$$Y(i, t) = \sum_{j=1}^{g_i} (1.5 - act(G_i(j), t))$$

with $S_i(j)$ a node connected with i through an S-relation and $G_i(j)$ a node connected with i through a G-relation.

5. Simulations.

Both process models were used to simulate experiments, which are reported in van Leeuwen & Buffart (1988) and in van Leeuwen et al. (1988). Each experiment is characteristic for a series of experiments, so that the three simulations are dealing with different phenomena of perception and retrieval of serial objects.

The chosen values of the parameters P and Q, which determine the rate of the increase and decrease of the activation values, will be in both process models and in all simulations the same, namely $P = 10$ and $Q = 50$. In practice we found that with these values for P and Q no extreme activation values were reached and that the mean activation value in the network remained around 0.5.

5.1. Simulation 1.

In Experiment 5 of van Leeuwen et al. (1988) four series of coloured dots are used, described by the patterns in (5). The pattern S_1 is the mirror image of S_2 and also is U_1 the mirror image of U_2. Subjects had to compare two consecutive presented series and tell whether they are identical (notation: IDE), like the pair $S_1 - S_1$, mirror images (notation: MIR), like the pair $U_2 - U_1$, or neither (notation: NEI), like the pair $U_1 - S_2$.

'*AABAABC*' (S_1)	'*CBAABAA*' (S_2)	(5)
'*ABBABBC*' (U_1)	'*CBBABBA*' (U_2)	

For each pattern there is a representation which describes all identity-relations in the pattern, namely '*xxyxxyz*' for S_1, '*zyxxyxx*' for S_2, '*xyyxyyz*' for U_1 and '*zyyxyyx*' for U_2. The first two

representations have 5 G-relations and 18 S-relations, while the last two representations have 6 G-relations and 18 S-relations. Because in both process models it holds that the activation value of a representation decays slower when it has less G-relations than the others, the representations of the patterns S_1 and S_2 are called relatively *stable* compared to the relatively *unstable* representations of the patterns U_1 and U_2. On the basis of this difference in decay it was theoretically predicted that the patterns with stable representations would be better memorized than the patterns with unstable representations. The sixteen possible pairs of patterns were divided in six categories, based on the difference in stability and the three possible response alternatives, see Table 4. The stable categories were formed by the pairs in which a stable pattern is always presented first. In general was predicted that the comparison of the pairs in the stable categories would be better than in the corresponding unstable category.

	IDE		MIR		NEI			
Stable	S_1-S_1	S_2-S_2	S_1-S_2	S_2-S_1	S_1-U_1	S_1-U_2	S_2-U_1	S_2-U_2
Unstable	U_1-U_1	U_2-U_2	U_1-U_2	U_2-U_1	U_1-S_1	U_1-S_2	U_2-S_1	U_2-S_2

Table 4. The sixteen possible pairs of patterns devided in six categories.

In the experiment six colour variations of each pair of patterns was, after a training with six pairs of patterns, presented twice to a subject in a random sequence, which gives a total of $6\times16\times2=192$ presented pairs of patterns. Table 5 shows for each category the mean number of correct answers given by the subjects, which are in accordance with the prediction.

Experimental results

	IDE	MIR	NEI
Stable	22.13 (0.28)	20.91 (0.62)	18.87 (0.75)
Unstable	20.52 (0.62)	18.66 (0.85)	17.04 (0.90)

Table 5. Experimental results in Simulation 1, expressed in the mean number of correct answers in each category (24.00 = 100 % correct), with the standard error between brackets.

We simulated this experiment by following the presentation procedure step by step. Just as in the experiment we presented six training pairs of patterns, followed by the 192 pairs of patterns in a random sequence. In this experiment a response is required after each pair of patterns. We use the sum of the activation values of the corresponding representations as a memorization measure, for predicting the comparison of the patterns by a subject. By using this measure we assume that a subject will make less errors as the sum of these activation values is higher. The mean memorization measure for all pairs in each category are reported in Table 6.

Process model 1				Process model 2			
	IDE	MIR	NEI		IDE	MIR	NEI
Stable	1.3174	1.1065	1.0509	Stable	1.3754	1.1774	1.1373
Unstable	1.2259	1.0181	1.0174	Unstable	1.3078	1.1257	1.1051

Table 6. Results of Simulation 1 for both process models, expressed in the mean memorization measure.

Comparing the mean number of correct answers with the mean memorization measure in each category, we find a correlation of 0.87 ($t(4)=3.54$; $p<0.02$) for the first process model and a correlation of 0.86 ($t(4)=3.30$; $p<0.03$) for the second model.

5.2. Simulation 2.

Experiments 1 and 2 in van Leeuwen & Buffart (1988) investigated the influence of a *cue* at the reproduction of *ambiguous* and *unambiguous* series. A series is called ambiguous if there are several stable representations, which describes a perceptible structure in the series. Otherwise, it is called unambiguous. By a stable representation we mean a representation with relatively less G-relations and relatively more S-relations.

Six series of eight coloured dots were used, whose structure is described by the patterns in (6). These six series form three pairs. Each pair consists of an ambiguous and a unambiguous series, which are almost equal except for the last two elements. The same colours are used in both series of a pair and they are not used in the other pairs. In the experiment one series at a time was presented. For half of the subjects the initially presented series were equal to the three ambiguous series, while the other half of the subjects started with the three unambiguous series. All subjects were instructed to learn these series. Thereafter, a sequence of 60 trials followed, in which each trial consisted of the presentation of a cue, whereupon the subject had to reproduce the corresponding learned series. This learned series could be reproduced by selecting a number of coloured dots out of a big heap of single dots, and putting them in the right order. During the sequence of trials at regular moments, according to a complex presentation scheme (see Table 2 in van Leeuwen & Buffart, 1988), a series was presented, which formed a pair with one of the learned series. From that moment on, this new presented series had to be reproduced on the appearance of the cue, instead of the earlier learned one. In this way the set of three learned series was changed several times during the experiment.

Ambiguous :	'*AABBABBA*'	'*CDCCDCCC*'	'*FGGFFGFF*'	(6)
Unambiguous :	'*AABBABAB*'	'*CDCCDCDD*'	'*FGGFFGGG*'	

In Experiment 1 the cue was equal to the first three elements of a series, so the ambiguous and the unambiguous series in a pair both had the same cue. Experiment 2 was almost identical to Experiment 1, except that in this experiment the cue was equal to only the first element of a series. This cue is called a *colour-cue*, because the cues for the three pairs only differ in their colour. This is opposite to Experiment 1, where beside the colour the structure of the cue can also be perceived. This cue is called a *structure-cue*. Van Leeuwen & Buffart (1988) argued that by presenting a structure-cue the unambiguous series would be reproduced better than the ambiguous series, while this would be the other way around in the experiment with a colour-cue. The prediction was based upon the expectation that perceiving the structure-cue will increase the activation values of representations of the pattern that had to be reproduced. It was argued that if

a structure-cue was presented the few stable representations of an unambiguous pattern were all increased by the cue, while this would not be the case for all stable representations of a ambiguous pattern. Table 7 shows the mean proportion of correct reproductions[4] in both experiments, which prove that the prediction was correct.

Experimental results (structure-cue)

	'AAB'	'CDC'	'FGG'
Ambiguous	0.52 (0.22)	0.56 (0.19)	0.50 (0.21)
Unambiguous	0.67 (0.23)	0.56 (0.19)	0.65 (0.20)

Experimental results (colour-cue)

	'A'	'C'	'F'
Ambiguous	0.51 (0.26)	0.57 (0.31)	0.36 (0.29)
Unambiguous	0.41 (0.22)	0.50 (0.26)	0.38 (0.20)

Table 7. Experimental results in Simulation 2, expressed in the mean proportion of correct reproductions (1.00 = 100 % correct), with the standard error between brackets.

We simulate both experiments by following the presentation scheme of van Leeuwen & Buffart exactly. In order to compare the experimental results with the results of the simulation, we have to formulate a measure for the reproduction of a pattern. Therefore, we assume that for reproducing a pattern a subject will only make use of the highest activated representations as far as they are necessary to memorize the structure of the pattern. This is in accordance to the view that knowledge is distributed stored in networks (McClelland & Rumelhart, 1985). In Simulation 1 this meant that for a pattern we could simply use the activation value of the corresponding representation, because for each pattern there is exactly one representation that describes the structure completely. This is not the case in this simulation, as for the ambiguous and even for the unambiguous patterns there is no representation that describes the structure completely. Therefore, we first select the representation with the highest activation value out of the set of representations that describes a structure in the pattern that has to be reproduced. If this representation does not describe the structure of the pattern completely, which is the case for all patterns used here, we also select the representation with the second highest activation value. If the structure of the pattern is still not completely covered by the combinated structure described by these two representations, we continue to select representations until the structure of the pattern is covered completely. The mean activation value of the selected representations is used as the reproduction measure of the pattern. The results of the simulations for both process models, expressed in the mean reproduction measure for each pattern, are shown in Table 8.

[4] The reported results in van Leeuwen & Buffart (1988) of both experiments are expressed in the mean number of errors in the reproduction of a series as well as in the mean number of confusions. However, for consistency with the other simulations, we report here the mean proportion of correct reproductions.

Process model 1 (structure-cue)

	'AAB'	'CDC'	'FGG'
Ambiguous	0.3896	0.3821	0.3631
Unambiguous	0.3748	0.3669	0.3460

Process model 2 (structure-cue)

	'AAB'	'CDC'	'FGG'
Ambiguous	0.3566	0.3665	0.3378
Unambiguous	0.3547	0.3320	0.3307

Process model 1 (colour-cue)

	'A'	'C'	'F'
Ambiguous	0.3896	0.3821	0.3631
Unambiguous	0.3748	0.3669	0.3460

Process model 2 (colour-cue)

	'A'	'C'	'F'
Ambiguous	0.3425	0.3523	0.3235
Unambiguous	0.3389	0.3177	0.3162

Table 8. Results of Simulation 2 for both process models, expressed in the mean reproduction measure.

By comparing the mean proportion of correct reproductions in the two experiments with the mean reproduction measure in the simulation, we find a correlation of 0.16 ($t(10)=0.52$; $p<0.62$) for the first process model and of 0.52 ($t(10)=1.92$; $p<0.08$) for the second model.

From these correlations it follows that the first process model is not capable to simulate these experiments. There is even not the slightest difference between results of the experiment with the colour-cue and the experiment with the structure-cue. This is due to the fact that in this model the activation values have no influence on each other. As the prediction in these experiments was just based upon the influence of the strength of the representations of the cue on the strength of the representations of the pattern that had to be reproduced, it is no surprise that the first process model is not capable to simulate these phenomena. However, Simulation 1 did show that the first process model is a good approximation of the behaviour of a subject, as long as the mutual influence between activation values of representations is not dominating.

But also the correlation for the second process model is, though significant, considerably lower than in the previous simulation. A possible explanation for this is that in the experiments colour was uniquely bound to a pair of series, in order to distinguish the colour-cues. This aspect, which is especially in the experiment with the colour-cue not unimportant, can not be simulated by our process models, as the strength of a representation depends only on the structure of the presented objects. An other explanation is that a subject is also influenced by what he or she perceives during the reproduction of a series. It is possible that through perceiving the already reproduced part of the series, some representations are extra strengthened. As we may assume that in the experiment with the structure-cue a subject starts to reproduce the cue, especially the representations of the cue are extra strengthened. This aspect is not simulated and that is perhaps the reason why the representations that had to be strengthened by presenting the structure-cue did not reach an activation value high enough to be included in the reproduction measure. This could be corrected for example by presenting the cue two or three times in the simulation, but this kind of ad-hoc solutions are not desirable. A more realistic solution would be a step by step simulation of the reproduction behaviour of a subject, but this is impossible for the existing experiments since we do not have reports of the steps. Nevertheless, we showed with this simulation that there is a difference between the two process models and that this difference is in favour of the second model.

5.3. Simulation 3.

Experiment 1 in van Leeuwen et al. (1988) investigated the reproduction of series influenced by the direction in which they are read. Therefore, series of coloured dots were placed along the border of a disk, which was in an envelope. This envelope partially covered the disk in such a way that only a few dots were visible at the same time through a window, see Figure 4. The three (or four) different series on a disk were separated by a space with the same size of a dot. Through the window were always nine elements – dots or spaces – of the disk visible. The subjects could inspect the disk by rotating it for 60 seconds, but they were only allowed to turn it counterclockwise. After the inspection, the subjects had to reproduce the disk by selecting the proper segments out of a set of segments, from which several disks could be reproduced, and putting them together correctly. By presenting disks with the mirror images of the same series to other subjects, it could be investigated how the reading direction influences the reproduction.

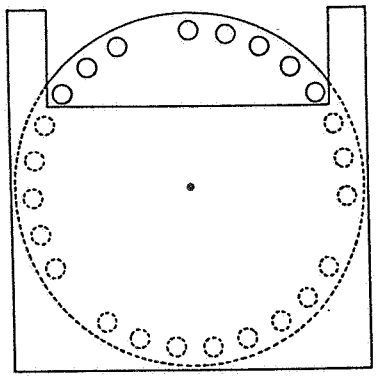

Figure 4. A disk with series of coloured dots in an envelope with a window.

The series on the four disks A, B, C and D are described by the patterns in (7). According to the theoretical predictions in van Leeuwen et al. (1988) a subject could reproduce a disk with these patterns better than a corresponding disk with the mirror images. The results of this experiment, expressed in the mean number of correct segments for each disk, see Table 9, show that this prediction was correct.

A :	*'ABCBAC'*	B :	*'ABCCBC'*	C :	*'AABACAAA'*	D :	*'AABBAABA'*	(7)
	'DEFEDE'		*'DEEEDE'*		*'DEFDEFED'*		*'DEDEDEEE'*	
	'GHIGHG'		*'GHHGHH'*		*'GGHHIIHG'*		*'GHHHGHHI'*	
			'KKKKLK'					

Experimental results

	A	B	C	D
Originals	4.67 (0.49)	4.19 (0.19)	5.00 (0.27)	5.38 (0.32)
Mirror images	2.83 (0.54)	3.28 (0.28)	4.13 (0.30)	4.13 (0.55)

Table 9. Experimental results in Simulation 3, expressed in the mean number of correct segments for each disk (6.00 = 100 % correct), with the standard error between brackets.

The experimental conditions were such that there were always two patterns presented at the same time, namely the last dots of a series and the first dots of the next series. In order to simulate this correctly, we have to change the input for the process models in comparison with Simulation 1 and 2, so that it will be possible to present several patterns at the same moment. This change implies that a node will be confirmed if its structure fits with at least one of the presented patterns. With this adaptation we can simulate this experiment by presenting the parts of the two series that are visible at the same time through the window of the envelope. If we assume that at each moment the disk is rotated exactly one dot, then for example the disk A with the original patterns and the corresponding disk with the mirror images are presented as in Table 10.

t	Originals	Mirror images
1	' ABCBAC D'	' CABCBA E'
2	'ABCBAC DE'	'CABCBA ED'
3	'BCBAC DEF'	'ABCBA EDE'
4	'CBAC DEFE'	'BCBA EDEF'
5	'BAC DEFED'	'CBA EDEFE'
6	'AC DEFEDE'	'BA EDEFED'
7	'C DEFEDE '	'A EDEFED '
8	' DEFEDE G'	' EDEFED G'
9	'DEFEDE GH'	'EDEFED GH'
10	'EFEDE GHI'	'DEFED GHG'
11	'FEDE GHIG'	'EFED GHGI'
12	'EDE GHIGH'	'FED GHGIH'
13	'DE GHIGHG'	'ED GHGIHG'
14	'E GHIGHG '	'D GHGIHG '
15	' GHIGHG A'	' GHGIHG C'
16	'GHIGHG AB'	'GHGIHG CA'
17	'HIGHG ABC'	'HGIHG CAB'
18	'IGHG ABCB'	'GIHG CABC'
19	'GHG ABCBA'	'IHG CABCB'
20	'HG ABCBAC'	'HG CABCBA'
21	'G ABCBAC '	'G CABCBA '
(1 =) 22	' ABCBAC D'	' CABCBA E'
etc.	.....	.....

Table 10. The patterns that are visible by rotating the disk A with the originals and the corresponding disk with the mirror images.

In the simulation, we assume that a subject usually starts the rotation of a disk at a moment when a complete series is visible (in the example at $t = 1$, 8, 15 or 22), and stops the rotation at a moment just after a complete series is inspected (in the example at $t = 2$, 9 or 16). Finally we

assume, based upon the experimental findings, that a subjects rotates a disk no more than three times in the inspection period of 60 seconds.

To measure the reproduction of a pattern at a disk we use the reproduction measure as formulated in Simulation 2. For the reproduction measure of a whole disk we take the sum of the reproduction measures of all patterns at the disk. The results of the simulation for both process models, expressed in the mean reproduction measure of a disk, are shown in Table 11.

Process model 1

	A	B	C	D
Originals	1.4209	1.9892	1.0427	1.3752
Mirror images	1.4209	1.9892	1.0427	1.3752

Process model 2

	A	B	C	D
Originals	1.5137	2.2721	1.0131	1.3700
Mirror images	1.5113	2.2707	1.0099	1.3688

Table 11. Results of Simulation 3 for both process models, expressed in the mean reproduction measure of the disks.

For the first process model we find no difference between the results of a disk with original patterns and a corresponding disk with the mirror images. The explanation for this is again the fact that in this process model the activation values have no mutual influence on each other. But for the second process model we find, in accordance with the experimental results, that the reproduction measure of a disk with original patterns is always higher than the reproduction measure of the corresponding disk. We can not present a meaningful correlation with the results of the simulations, because, unfortunately, the experimental results of the disks are not mutually comparable. This is due to the fact that in the experiment the set of segments, from which a disk had to be reproduced, was different for each disk, so the mean number of correct segments is always a relative score in respect to the set of segments for that specific disk.

6. Discussion.

Although the above experiments differ in presentation, task and type of response, they all can be simulated by the 'Structural Memory'. As the presentation procedure is always followed carefully step by step, we may call our simulations *realistic*. This is an important plus-point, because many models, especially in the artificial intelligence like SOAR (Laird et al., 1987) or SHRDLU (Winograd, 1972), fail in the exact imitation of the behaviour of subjects in real situations. It is therefore interesting to point out that in our least realistic simulation (namely Simulation 2, where the colour aspect and the perception during the reproduction could not be discounted), we also got relatively the least results.

Another important aspect in our simulations is the possibility to use the same output measure for different experiments. In all simulations we defined the output upon the principle that the number of used activation values has to be minimized. In Simulation 1 it was sufficient to use the activation value of just one representation. In Simulation 2 and 3 this principle gives the reproduction measure, i.e. the mean activation value of the highest activated representations as far as they are necessary to reproduce the pattern. When we drop our principle, we can also use this reproduction measure for Simulation 1. The results are still reasonable, because there is a correlation between the experimental and simulated results of 0.82 ($t(4)=2.84$; $p<0.05$) for the first process model and of 0.70 ($t(4)=1.98$; $p<0.12$) for the second model. By using always the same measure a separate procedure for generating output (Ratcliff, 1978) is unnecessary. The

disadvantage of such an output procedure, namely that it has to be adapted to each specific task and therefore its parameters have to be estimated from the samples, is in our opinion larger than the advantage that not only predictions for the percentages correct answers, but also for their distribution could be made.

Summarizing, the 'Structural Memory' is capable to simulate in a realistic way different dynamical phenomena, without adaptation of parameters, by a process model in which the same output can be used. From this we can conclude that the network structure is a good basis for a process model. Because of the found relation between the number of G- and S-relations and the I-load of a representation, such a process model will give about the same predictions as the economy principle, when there is no influence of the earlier perceived objects. And if this influence is important, it still gives good predictions, as we saw from the results of the simulations. Besides, the more realistic process model 2 performed reasonable in all three simulations, whereas the first model performed well in Simulation 1 only. This shows that a process model can not forego on the dense interactions between individual nodes (Skarda & Freeman, 1987). Therefore, we conclude that the network structure is more important than the exact formulation of a process model. As long as a process model is based upon the network structure and as long as the activation values have influence on each other, the 'Structural Memory' will be capable to simulate human perception of serial objects.

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