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About a framework for information and information processing of learning systems

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Abstract
Information and information processing are one of the most important aspects of dynamic systems. The term 'information', that is used in various contexts, might better be replaced with one that incorporates novelty, activity and learning. Many important communications of learning systems are non-ergodic. The ergodicity assumption in Shannon's communication theory restricts his and all related concepts to systems that can not learn. For learning systems that interact with their environments, the more primitive concept of 'variety' will have to be used, instead of probability. Humans have a fundamental need for variety: he can't permanently perceive the same context, he can't do always the same things. The fundamental need for variety leads to a different interpretation of human behaviour that is often classified as "errors". Variety is the basis to measure complexity. Complexity in the relationship between a learning system and his context can be expressed as incongruity. Incongruity is the difference between internal complexity of a learning system and the complexity of the context. Traditional concepts of information processing are models of homeostasis on a basic level without learning. Activity and the irreversible learning process are driving forces that cause permanently in-homeostasis in the relationship between a learning system and his context. A suitable model for information processing of learning systems must be conceptualised on a higher level: a homeostatic model of 'in-homeostasis'. A concept to information processing is presented that derives an inverted U-shaped function between incongruity and information. This concept leads to some design recommendations for man-machine systems.

Keywords
Information, information processing, learning, activity, complexity, incongruity, variety

1 INTRODUCTION

We live in a dynamic and irreversible changing world. We are information processing systems and have a huge learning potential. What happens to humans, if they have to behave in an approximately static environment? If we need growth (in a psycho-dynamic sense) and development, how long we are able to tolerate contexts that fix and constrain our activities? There is a lot empirical evidence that humans are getting bored if the context is characterized by repetitiousness, lack of novelty, and monotony (Smith 1981). Ulich (1987) differentiates between boredom and monotony. Boredom emerges from the feeling of not having enough possibilities to be active. Monotony emerges from the feeling of doing always the same

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things. "Monotony is a consequence of standardisation of the work process" (Ulich 1987, 8). On the other side, there is strong empirical evidence of stressed and over-loaded workers (Hockey 1983).

We have to realise and to accept that humans do not stop learning after end of school. We are compelled to learn and to make experiences our whole life. Human information processing can not be independent of this life-long learning process. In this sense, humans are open systems. In his law of requisite variety Ashby (1958) pointed out, that for a given state of the environment, an open system has to be able to respond adaptively, otherwise the adaptability and the ability of the system to survive is reduced. A learning system, without input or with constant input, either decays or (in the best case) remains the same. Learning and the need for variety implies, that with constant input variety the requisite variety of the system tends to decay over time. This is a strong argument against 'one best way' solutions in work design on a structural level (see also Ulich 1987).

2 CONCEPTS OF INFORMATION

We can find in the literature different interpretations of the term 'information' (see Table 1). Several approaches from different point of views are done to clarify 'information' (e.g., Topsøe 1974, Dörner 1979, Folberth & Hackl 1986, Völz 1991 and Fuchs-Kittowski 1992).

Table 1 Survey of six interpretations of 'information' found in the literature

1.) Information as a message	(syntax)
2.) Information as the meaning of a message	(semantic)
3.) Information as the effect of a message	(pragmatic)
4.) Information as a process	
5.) Information as knowledge	
6.) Information as an entity of the world	

If we try to apply information theory to human behaviour, then we have to integrate activity, perception, and learning. In this proposal we are looking for an interpretation of 'information', which is compatible with concepts of activity and learning. Going this way, we hope to avoid the paradox of 'new' information. Information before and after the reception of a message is not the same! Different concepts are introduced to 'solve' this paradox (see Table 2).

Table 2 Terms to describe the amount of information of a message before and after reception

before reception	*after reception*	*Author*
degree of freedom of the decision	content of the decision	HARTLEY 1928
uncertainty	certainty	SHANNON 1949
uncertainty	information	BRILLOUIN 1964
potential information	actual information	ZUCKER 1974
entropy	amount of information	TOPSØE 1974
information	exformation	NØRRETRANDERS 1991

Streuffert and Streuffert (1978, 105) differentiate between 'information load' (the quantity of information per unit time), 'eucity' (the success component of information), and 'noxity' (the failure component of information). "Where noxity requires taking an action over again, thereby increasing current load by adding action requirements, eucity is likely to decrease load. Irrelevant information will be equivalent to load only with regard to some of the activities in which a person is engaging at the present time" (Streuffert and Streuffert 1978, 105).

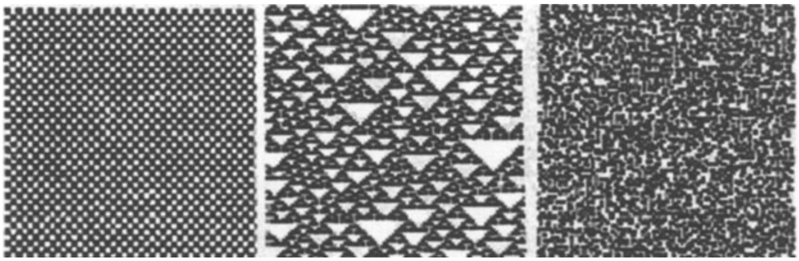

Figure 1 Three visual pattern of increasing 'entropy' or 'information' from left to right.

The modern discussion of information and complexity in the context of physics (cf. Zurek 1991) is based on the following paradox: Nearly all measures of information increase monotonously with complexity of the stimulus pattern (see Figure 1; cf. Grassberger 1986). But, the subjective impression of each observer is that the middle pattern contains the maximum of information, and not the left or the right pattern! There must be an inverted U-shaped function between subjective 'information' and the information measured by entropy or complexity. The approaches of the physicists to overcome this paradox seem to be not convincing, because most researchers in this community are constrained by their implicit goal to look for an *observer independent* solution (cf. Crutchfield and Young 1991).

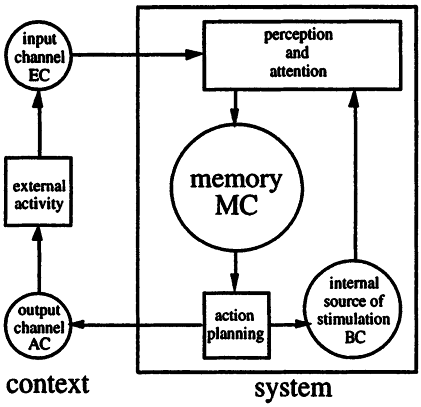

Figure 2 Two different sources for perception: the 'input channel' of the context and the 'internal source of stimulation' of the system.

The concept proposed in this paper assumes, that information processing is an interactive concept and observer dependent. We also try to enclose perceptual and behavioural aspects. We suppose further on, that the stimulus effects of the environment (or context) interact with the real or potential complexity of the receiver. The context can be (1) the environment beyond the human skin, (2) the neural stimuli of extremities (e.g., arm and leg movements, motor restlessness), and (3) mental processes like 'daydreaming', etc. We call all perceivable stimuli that are generated *inside* the system, the 'internal source of stimulation' (see Figure 2). So, the complexity of the context (CC) is the sum of the environmental complexity (EC) and of the bodily complexity (BC; e.g., measured by the level of arousal). The complexity of the receiver is limited to the internal complexity of his task related memory or mental model (MC).

At least, we have a human in mind that is motivated to attend to the stimuli and is motivated to respond in some meaningful fashion to the situation of which the stimuli are a part. Attention as one perceptual aspect is closely coupled with arousal.

3 AROUSAL AND ATTENTION

The fundamental law that relates performance to arousal is the Yerkes-Dodson law (Yerkes and Dodson 1908). This 'law' stated that the quality of performance on any task is an inverted U-shaped function of arousal, and that the range over which performance improves with increasing arousal varies with task complexity. A simple task needs a higher amount of arousal than a more complex task to reach a maximal quality of performance. We can conclude that there is -- overall at the time -- a limited capacity to handle complexity. The limit is the sum of two parts: (1) the contextual complexity CC (e.g., a given task complexity EC and/or a given level of arousal BC); and (2) the internal complexity of the memory MC.

If the external complexity of the environment EC decreases, then the complexity BC must increase to guarantee optimal quality of task performance. To increase BC, Smith (1981) describes various 'coping' strategies: drugs (e.g., caffeine, nicotine), motor restlessness, daydreaming. So, human perception of contextual complexity can be affected either by the content of the external 'input channel', or by the content of the 'internal source of stimulation' (see Figure 2). Now we can very easily relate the typical effects of drugs to three types of intended stimulation: (1) increase of action planning and activity (AC: e.g., cocaine), (2) increase of internal stimulation (BC: e.g., caffeine, nicotine), and (3) increase of perceptual range of the input channel (EC: e.g., LSD).

On one side, the external complexity EC can be increased through activity (AC, see Figure 2): exploration, response variability, and -- as last possibility -- withdrawal from boring situation. On the other side, Dörner et al (1988) assume that arousal correlates with the whole 'mental set of actual intentions' (MSI). If this assumption is correct, then we deduce that the complexity of MSI is an important part of BC. Stress through 'informational' overload is the increase of BC caused by the enhancement of MSI complexity. The empirical evidence reviewed in Kahneman (1973, 28-42) suggests that a state of *high arousal* is associated with the following effects: "(1) narrowing of attention; (2) increased liability of attention; (3) difficulties in controlling attention by fine discriminations; and (4) systematic changes of strategy in various tasks." Kahneman relates attention only to the external 'input channel' (EC, see Figure 2). So, if the perceived complexity of the 'internal source of stimulation' (BC) is high (e.g., high arousal), then the perceptual capacity of the external 'input channel' (EC) is low (e.g., narrowing of attention, loss of fine discriminations, cf. Hockey 1983, chapter 1).

On the other side, a state of extremely *low arousal* may cause: (1) a failure to adopt a task set; (2) a failure in the evaluation of one's performance, resulting in an insufficient adjustment of the investment of capacity to the demands of the task. We will see later, that humans in a state of extremely low arousal primarily try to cope with this situation by increasing stimulation (external and/or internal) or, if an increase is not possible, escaping.

4 ATTENTION AND ACTIVITY

To determine the point of visual attention, several studies measured eye movements. There are much unsolved problems to correlate eye movements with higher psychological processes. But, 'eyes as output' are one of the best empirical sources. Kahneman (1973, 64-65) distinguishes three types of eye movements:

(1) *Spontaneous looking*, which is governed by the so-called 'collative' features of stimuli (novelty, complexity; see Berlyne 1960). Responses to such stimuli are 'enduring dispositions', rooted in the innate tendency to respond to contours, and toward moving objects.

(2) *Task-relevant looking* is viewed as an allocation problem. It is a characteristic of the eye in that it has sharp vision at its centre or fovea, while peripheral vision is increasingly less distinct on outwards. Parafoveal vision is very sensitive to movements. Sharp vision occurs in sequential glances. The problem of where next to look is resolved through the interaction of task constraints and the visual context.
(3) Looking is a function of the *changing orientation of thought*. Eye movements of this type seem to reflect the overall transitions between stages of thought, even when the location, where the human is looking, cannot possibly offer any 'new' information. The eye movements during thought seem somehow to be related to the balance of activity between the two hemispheres, the rate of mental activity generally.

Brown and Gregory (1968, 810) concluded from their experimental results for attentional responses of humans to visual patterns, "that time spent viewing non-representational patterns: (a) increases as complexity, and especially the amount of contour defining the pattern, increases; and (b) roughly describes an inverted U-shaped function with increasing amounts of 'information' (a term which might better be replaced with one which incorporates novelty and related concepts with information-theoretic concepts), with the course and peak of the function being governed by the point(s) at which the observer alters the 'level of exactness' at which he abstracts the information."

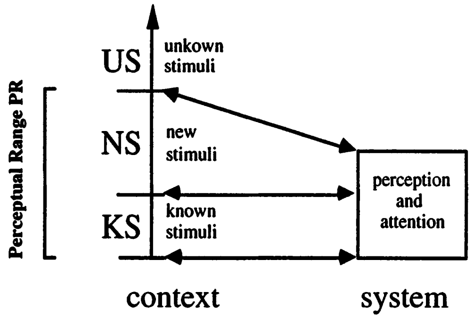

Figure 3 The three parts of the context that relate to perception: known structures (KS), new structures (NS), and unknown structures (US).

The range of perceivable stimuli is divided into three parts: known structures and stimuli (KS), new structures and stimuli that are -- actually or potentially -- perceivable (NS), and unknown stimuli that are unknown and therefor not perceivable (US; see Figure 3). At the moment it is unclear, how to get the dividing line between NS and US. The dividing line depends probably on the stored knowledge and learning strategies. What happens, if practice and learning increase KS by chunking? If we assume, that KS plus NS is about constant and KS increases over time, then NS must decrease. This seems to be not very attractive, even if this can sometimes happen. Perceptual chunking means to reduce complexity in NS and to increase complexity in KS. We call the range of KS plus NS the 'openness to the whole context': the *perceptual range* (PR). The attention controls the selection and reconstruction process of stimuli in PR. An empirically good validated effect runs as follows: the longer you are looking on something, the more you are going into details. The transfer rate from NS to KS is probably correlated with the learning rate.

Neisser (1976) distinguish between 'available information' and 'potential available information'. It is unclear, which mapping to our three parts is correct: (1) 'available information' is KS plus NS, and 'potential available information' is US, or (2) 'available information' is only KS, and 'potential available information' is NS plus US. The most interesting question is: What does the transfer from US to NS look like? One possible answer is behavioural activity based on exploration or on supervised learning and training. Each activity is semantically underspecified! Nobody can foresee all unintentional side effects of his or her actions.

Attention depends strongly on our experience with the situation. Card (1982) could show that in man-computer interaction users form perceptual chunks as a result of practice. The same results are reported by Furst (1971). Möckl and Heemsoth (1984) proved the hypothesis that the degree of knowledge about a biological motion pattern (shot putting) determines the location of eye fixations. They found that the mean number of fixations at points with maximal information increased with increasing knowledge about the motion pattern. Points of maximal information were defined by an extra group of experts (coaches) about the performance of the motion. Thomas and Lansdown (1963) could show that radiologists have a more specific fixation pattern looking at a radiology picture than at an unknown ink blot.

From these empirical results we can derive two possible conclusions: (1) the amount of socialisation and experience is negatively correlated with openness to the whole context; or, (2) the amount of socialisation and experience reduces complexity of new stimuli (NS) through chunking to keep the rest of the perceptual range (PR) free for new and unknown stimuli. Following the last interpretation we can say that humans are self optimising systems, which try to adapt to the context (Reynolds and Jones 1978). The different attractors for optima are constrained by the various kinds of knowledge sources: culture, organisation, task, and parts of our genetic, psycho-physiological and mental structure. These sources determine what is important and what not, and where to turn attention to. In this sense we follow a 'soft' constructivistic perspective

In a first step we replace the term 'complexity' with the term 'incongruity'. Our second step is to relate 'information' to 'incongruity'. Finally we present a suggestive relationship between 'incongruity' and 'information' based on behavioural activities to incorporate novelty and learning.

5 ACTIVITY AND INCONGRUITY

Investigators of novelty assume, that living systems (like mammals, especially humans) are motivated by an information seeking behaviour. In situations, which are characterized by sensory deprivation, humans are intrinsically looking for stimulation. They increase the complexity of the context or the perception of it. On the other side, humans try to avoid situations with a high amount of stimulation, dissonance, or stress (cf. Reynolds and Jones 1978).

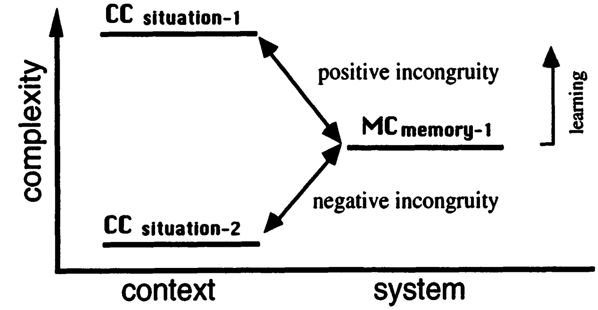

Figure 4 The difference between the complexity of the mental model and the complexity of the context is called incongruity.

Hunt (1963) designated the amount of increased complexity as 'incongruity'. We shift the semantic and theoretic problems from incongruity to complexity. Doing this, we can define incongruity in a more precise way. Incongruity (I) is the difference of contextual (CC) and internal complexity (MC, see Figure 4).

"Incongruity" $I := CC - MC$ (1)

If the complexity of the memory or mental model MC is less complex than the complexity of the context CC, then humans try to optimise this *positive incongruity*. Seeking and explorative behaviour starts, when the positive incongruity sinks below an individual threshold or changes to negative incongruity (deprivation). Behaviour of avoidance can be observed, when the positive incongruity exceeds an individual threshold (dissonance, stimulation overflow). Most of daily situations can be characterised by a certain degree of positive incongruity.

One unsolved problem is to find -- from the users' point of view -- a good measure for the complexity of the *perceived* context (the perceptual range PR). This problem is difficult, because we have to differentiate between the known and pre-structured part of perception based on learned mental schemata (KS) and the unstructured and not predictable part, which enable the human to integrate really new aspects (US) into the stored knowledge. Attention and learning influences directly the shift from US to KS.

6 THE MEASUREMENT OF COMPLEXITY

In man-computer interaction we are able to measure the complexity of human behaviour (e.g., explorative activities; see Rauterberg 1993). With some plausible assumptions we are also able to estimate the complexity of users' mental model (MC), too (see Rauterberg 1992). What is the main concern of a user interacting with a technical system? The user must build up a mental representation of the system's structure and gain knowledge about the task relevant functions of this system. Furthermore, he must learn the "language", i.e., a set of symbols, their syntax, and operations connected to them, to evoke interaction sequences (the interactive "processes") related to task and sub-task functions. Thus, the user's representations of the system structure are models of a virtual machine.

A "virtual machine" is defined as a representation of the functionality of a system (functional units and their behaviour). The most important point for the user is the relation between task and machine, rather than the internal structure of the machine's system. Consequentely, the task for the human factors engineer is to model a suitable interface as a representation of the virtual machine that can serve as a possible mental representation for the user.

The symbolic representation of the machine system consists of the following elements: 1. Objects (things to operate on), 2. operations (symbols and their syntax), and 3. states (the "system states"). The mental model of the user can be structured in representing objects, operations, states, system structure, and task structure.

6.1. The basic idea

Given a finite action space, each state corresponds to a system context, and each transition corresponds to a system operation. A trace (= sequence) of states and transitions in this action space can describe a complete or partial task solving process. Each finite trace in the action space is called a "process". A task solving process contains three different kinds of information: (1) all necessary states and transitions itself, (2) the amount of repetition of each necessary state and transition, and (3) the sequential order of all these states and transitions.

Finite state transition nets can be completely described with Petri nets, which have a clear semantic (Peterson 1981). A Petri net is a mathematical structure consisting of two non-empty disjoint sets of nodes, called S-elements and T-elements, respectively, and a binary relation F, called the flow relation. F connects only nodes of different types and leaves no node isolated. Petri nets can be interpreted by using a suitable pair of concepts for the sets S (signified by a circle "( )") and T (signified by a square "[ ]") and a suitable interpretation for the flow relation F (signified by an arrow "->"). The means/activity interpretation allows one to describe the static structure of a system with several active and passive functional components: means (S) = real or informational entity, and activity [T] = (repeatable) action of a system. The flow relation F signifies: [a] -> (m), the activity 'a' (e.g. a system operation) produces means 'm' (e.g. a system state); (m) -> [a], activity 'a' uses means 'm'.

The main operations (relations) between two nets are abstraction, embedding and folding (Genrich, Lautenbach and Thiagarajan 1980). The "folding" operation is the basic idea of the alternative approach presented in this paper. Folding a process means to map S-elements onto S-elements and T-elements onto T-elements while keeping the F-structure. The aim of the "folding" operation is to reduce the elements of an observed empirical task solving process to the minimum number of states and transitions, with the reduced number of elements being the "performance net". Folding a task solving process extracts the embedded net structure and neglects the information of the amount of repetition and of the sequential order (see Figure 5).

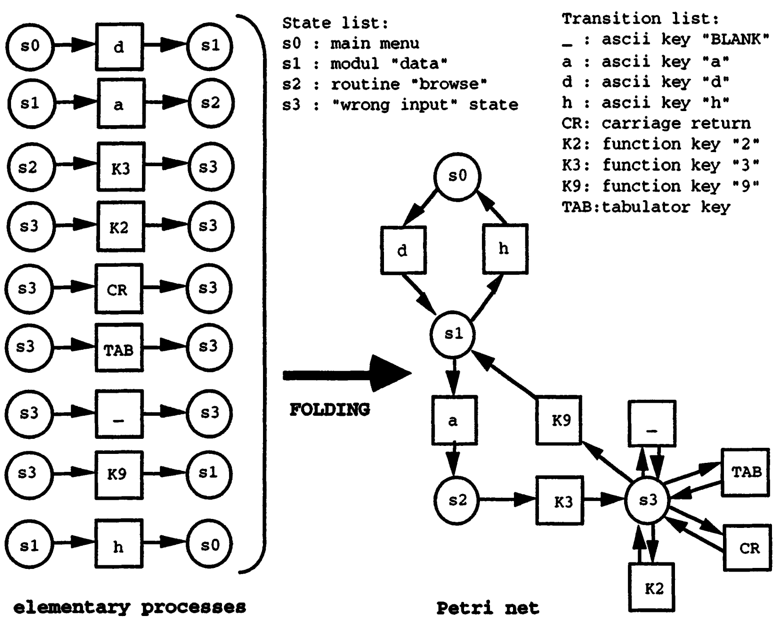

Figure 5 The nine observed elementary processes of an example process and the folded Petri net generated by AMME. Right side above: semantic labels of all states and transitions.

The shortest meaningful part of each process is an "elementary process": (s') -> [t'] -> (s"). If the observable behaviour can be recorded in a complete ...-> (state) -> [transition] -> (state) ->... process description, then the analysis and construction of the net structure of this process can be done by counting the number of all different states (#DS) and different transitions (#DT) used, or to mark the frequencies of each state and transition used in the process on a list of all possible states (transitions, resp.). But, if the observable behaviour can only be recorded in a more or less incomplete process description (e.g. ...-> (state) -> [transition] -> [transition] ->...; or ...-> (state) -> (state) -> [transition] ->...), then the analysis and construction of the net structure of this process are difficult: one has to find out the correct state (transition, resp.) between two transitions (states, resp.). Unfortunately, this is the most frequent case in practice. For these cases automatic tool support is necessary.

6.2. Net extraction with AMME

The program AMME (Automatic Mental Model Evaluator) is a tool which offers computer aided support in analysing incomplete recorded processes. This obstacle can be overcome with a description of the complete state transition space in advance, which can be used by the tool AMME to control the correct interpretation of the incomplete process description.

First of all the investigator has to define a *state list*: a complete description of all states of the interactive system. All possible transitions between different or equal states restrain the action space of the user. One special transition must be taken into account: the "empty" user action. This is the case when the system automatically changes from one state to another without any user input.

Second, the investigator has to determine a complete action list as a *pre-post state matrix*: a description of all allowed user actions (resp. transitions) changing the actual system state (pre state) to the post state; pre and post states can, but must not be different. The pre-post state matrix is a compact and complete description of all possible elementary processes in the action space.

The program AMME looks for all elementary processes in the sequence, counts the frequency of each observed elementary process to analyze first order Markov chains, and writes this information in the output file with the "frequency matrix". The composition algorithm (the folding operation) of AMME is now able to build up the embedded Petri net combining all observed elementary processes. The result of the folding operation of an example sequence is the Petri net given in Figure 5. This special net with four different states (#DS) and nine different transitions (#DT) is the minimal net structure we need to reproduce all elementary processes given in Figure 5. Each "folded" Petri net is a formal description ("model") of the observed performance of the user's behaviour.

6.3. Input and output files for AMME

The tool environment of AMME consists of four different programs: (1) the interactive system (e.g., with a logfile recording feature); this interactive system can, but must not be a computer; (2) the analysing program AMME, which extracts the net of the task and user specific processes and calculates different quantitative aspects of the generated net structure; (3) the Petri net simulator PACE (Dähler 1989), and (4) the analysing program KNOT (Interlink 1991; Schvaneveldt 1990). AMME needs two input files: (1.) the complete system description on an appropriate level of granularity (the complete state list and the pre-post state matrix), and (2.) the process description of a specific individual task solving process corresponding to the granularity level of the system description (see Figure 6). The process descriptions can be automatically generated by an interactive system (the "logfile recording" technique) or hand written by the investigator (e.g. based on protocols of observations). AMME produces five different output files (see Figure 6).

Analysing a set of different process descriptions with AMME is normally an iterative procedure, if the description of the total interactive system is quite large and therefore at the beginning incomplete. With each new process description analysed by AMME the input file with the provisional "complete" system description must then be updated with "new" states and/or transitions. After analysing the whole sample of process descriptions in the first trial all process descriptions must be re-analysed in a second trial. This procedure guarantees that the calculation of all quantitative measures of each analysed net is based on the same system description.

We call the complexity of the observable processes the "activity complexity (AC)" (see Figure 2). This activity complexity can be estimated by analysing the recorded concrete task solving process ("logfiles"). The complexity of a given work system (the "action space") we call "system complexity (SC)". The account of SC is given by the complete pre-post state matrix, which contains all possible elementary processes. The system complexity (SC) is approximately a valid measure for the external complexity (EC) in the context of human-computer interaction. The complexity (AC) of the observable processes of beginners should be on average larger than the complexity of the observable processes of experts.

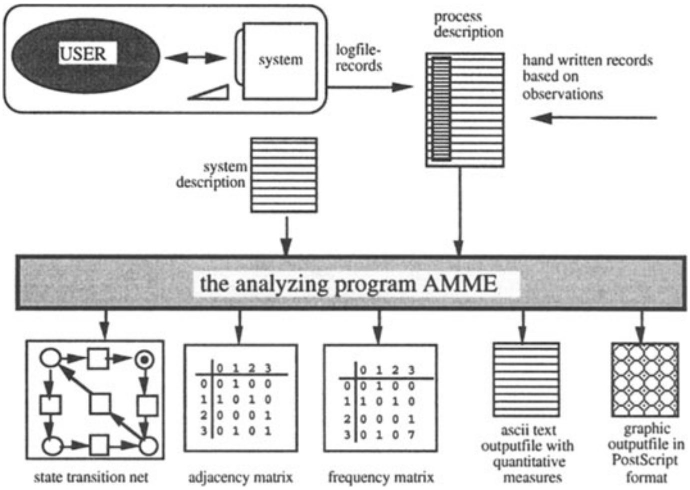

Figure 6 The analysing program AMME requires two input files and generates five different output files: (1) a net description for the Petri net simulator PACE, (2) an adjacency matrix for the Pathfinder software KNOT, (3) a frequency matrix to analyze first order Markov chains, (4) a plain text file with the quantitative measures, and (5) a graphic output.

6.4. Definition of complexity

One important difference between beginners and experts is the complexity of their mental model (Bainbridge 1991, 343). The beginners have a simple mental structure, so they have to behave in a more heuristic manner to operate an interactive system. On the other hand, the structures of the mental model of the experts are more or less correct representations of the system structure, so they can behave efficiently to solve given tasks. We therefore assume that the mental model of an expert is more comprehensive than that of a beginner. This assumption can be tested by comparing the complexity of the observable processes of beginners and experts.

To measure complexity we introduce the C_{cycle} metrics (the "cyclomatic number") of McCabe (1976). C_{cycle} is a measure to calculate the number of linear independent cycles of a plane and coherent net. C_{cycle} is a useful quantity that measures the amount of interconnectivity (complexity). The advantages and disadvantages of four different quantitative measures of complexity have been discussed in Rauterberg (1992); C_{cycle} proved to be the most effective measure.

The complexity measured with C_{cycle} is defined by the difference of the total number of connections (#F: flow relation) and the sum of the total number of states and of transitions (#S: state + #T: transitions). The parameter P is a constant that corrects the result of Formula 2 in the case of a sequence (#F – (#S+#T) = –1); the value of P in this context is 1. The semantic of C_{cycle} can be described by the number of "holes", "loops" or "cycles" in a net.

"Cyclomatic number" $C_{cycle} := \#F - (\#S + \#T) + P$ with P=1 (2)

The measure C_{cycle} of the net example in Figure 5 is #F – (#S+#T) + P = 18 – 13 + 1 = 6; the complexity of the underlying sequential task solving process is zero (a sequence has no cycles)!

6.5. Results and Conclusion

Cognitive complexity has been defined as "an aspect of a person's cognitive functioning, which at one end is defined by the use of many constructs with many relationships to one another (complexity) and at the other end by the use of few constructs with limited relationships to one another (simplicity)" (Pervin 1984, 507). Transferring this broad definition to human computer interaction could imply that the complexity of the user's mental model of the dialog system is given by the number of known dialog contexts ("constructs") on one hand, and by the number of known dialog operations ("relationships") on the other hand. To measure the complexity of a mental model which generates an observable process, a "mapping" procedure from the observable process description to the embedded structure of this process is necessary. This "mapping" procedure can be done with the folding operation in the context of Petri nets. The "activity complexity" of the folded net (based on the "cyclomatic number") is defined as:

"Activity complexity" $AC := \#F - (\#DS + \#DT) + 1$ (3)

We can show, that the complexity of the observable task solving behaviour (the "activity complexity"; AC) of beginners is significantly larger than the complexity of the observable behaviour of the experts (Rauterberg 1993). The difference between beginners and experts can be fully explained using the "task solving time" as a covariate in the analysis of variance, but not the differences among the four tasks. This is a strong hint, that the "activity complexity" (AC) depends only on task features.

The Spearman rank correlation (r) between the "total computer experience" (measured with a questionnaire) and the mean of AC (averaged over tasks) is: $r = -.682$ ($N=12$; $p \leq .02$). This important result indicates, that the complexity of the observable actions correlates negatively with the complexity of the cognitive structure (the "mental model"). So, the complexity of the necessary task knowledge can be either observed and measured with AC or is embedded in the cognitive structure. If the cognitive structure is too simple, then the concrete task solving process must be carried out with many heuristics or trial and error strategies. Learning how to solve a specific task with a given system means, that AC decreases and the complexity of the mental model increases (MC).

7 LEARNING AND ACTIVITY

Learning is a permanent process that changes our long-term knowledge base in an irreversible way. The structure of our long-term memory changes to more complexity and higher abstraction. Bateson (1972) developed a hierarchical concept of four different learning stages that reflects different levels of abstraction. The basic idea of Bateson's concept is that the variety on one level can be reduced to an *invariant structure*. This invariant structure forms the next higher, more abstract level of learning. Learning implies abstraction. Humans under non standardised and not fixed conditions evolve during their lifetime very abstract invariants. Actual research is done under the topic of 'meta-cognition' and 'meta-learning' (Weinert and Kluwe 1984). Learning as a driving force for irreversible developments is the most underestimated factor in human behaviour, especially in the work and organisational context.

Neisser (1976) was one of the first researcher, who tried to integrate activity, perception, and learning (see Figure 7). He emphasised that human experience depends on the stored mental schema, which guide explorative behaviour and the perception of external context. Learning increases constantly the complexity of the mental model (see Figure 4). This is an irreversible process. One consequence is, that the contextual complexity must increase appropriately to fit the human needs for optimal variety.

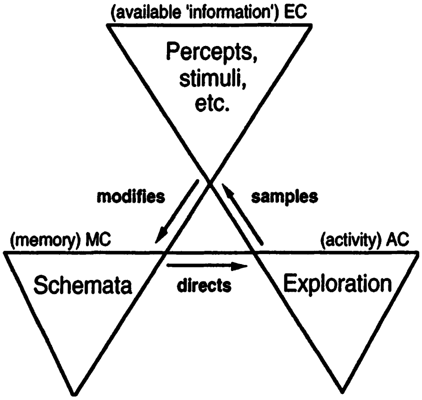

Figure 7 The perceptual cycle (following Neisser 1976, 21).

The empirical results in Rauterberg (1993) indicate, that the complexity (AC) of the observable processes of beginners is larger than the complexity of experts. We concluded that the activity complexity is negatively correlated with the complexity of the underlying mental model (MC). Thus it is possible to estimate the cognitive complexity based on the measurement of the activity complexity, the measurement of the system complexity (EC) and the measurement of the task complexity (for a more detailed discussion see Rauterberg 1992).

8 ACTIVITY AND INFORMATION

Weizsäcker (1974) differentiated the concept of 'information' into two aspects: (1) 'Singularity of the first time', and (2) 'confirmation and redundancy'. For both aspects we can find two different research traditions in psychology: (1) novelty and curiosity (Berlyne 1960, Hunt 1963, Voss and Keller 1981), and (2) dissonance theory (Festinger 1957, Irle 1975, Frey 1981). Both research tracks are only loose coupled till today. A context with sensory deprivation has not enough positive incongruity or even negative incongruity. On one side, a human will leave a context with very low incongruity (to little difference to context complexity), and on the other side with very high incongruity (to much context complexity; see Figure 8). In between we have the range of positive emotions with behaviour, which increase novelty on one side, and on the other side that increase confirmation and redundancy, or reduce dissonance.

Paritsis and Steward (1983) considered that the needs of "Natural Intelligent Systems" for information and variety can change according to the rate of their satisfaction. They argue that humans are seeking satisfaction and development, and that there is a *need for information* and variety, which facilitate development. This need for variety and the relationship to satisfaction is also valid in work contexts. "The most common source of interest is variety" (Walker and Marriott 1951, 182). Paritsis (1992) suggests that there is an optimum variety, which maximises the rate of development and evolution. Ulich (1974) expects the same relationship between task complexity and the efficiency of work. In particular for a given human, context and time is an optimum variety (and information) in the context, "which is a) as low to enable the organism to be adapted on the basis of its requisite variety, b) as high to allow and induce development, c) at the same time does not produce overload or under-load stress" (Paritsis 1992, 35).

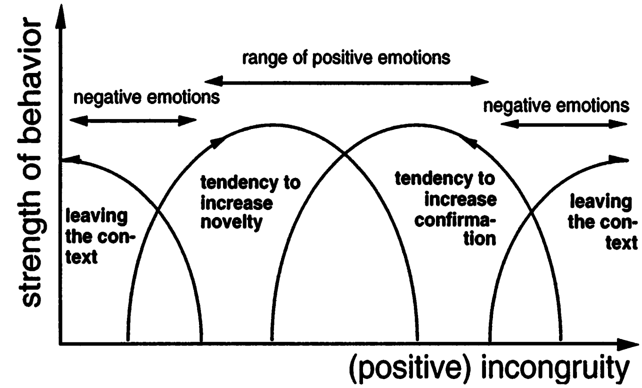

Figure 8 The coherence between positive incongruity, emotions and observable behaviour (following Streuffert & Streuffert 1978, 201).

Overall we assume a reverse U-curve as the summarised coherence between incongruity and information (see Figure 9). If a human has to behave for a while in a total fixed and stabile context and he has a normal learning rate, then -- after a while -- he must start to increase the incongruity. This can be done on two different ways: (a) increasing the complexity of the context or the perception of it, and/or (b) reducing the complexity of the mental model. Way (b) implies the possibility of 'forgetting', decrease of the learning rate or the manipulation of the perception mechanisms (suppression). Way (a) is often preferred and is characterized by exploratory behaviour (the 'tendency to increase novelty', see Figure 8).

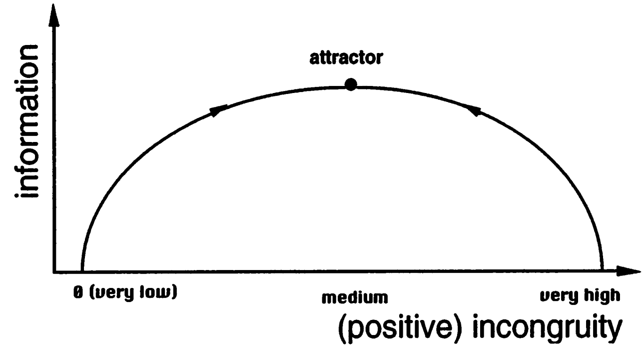

Figure 9 The summarised coherence between positive incongruity and information.

The structure of our long-term memory changes itself -- caused by learning -- to more complexity and higher abstraction (cf. Figure 4). This dependency was empirical investigated by Raab and Ebner (1982). Raab and Ebner presented musical stimuli of different complexity (EC) to three groups of different mental complexity (MC: experience with music): (a) technical students with low experience, (b) students of pedagogy with medium experience, and (c) students of music with large experience. Raab and Ebner got two important results: (1.) The subjective ratings of the 'informativeness' of the stimuli have an inverted U-shaped function in relation to the complexity of the stimuli, and (2.) the optima of the inverted U-shaped functions are different between groups; the optimum depends on the amount of experience.

Boreham (1993, personal communication) described the different reactions of nurses and high qualified physicians in a monitoring task during anaesthetisation. Humans with lower cognitive complexity (e.g., nurses) are more able to be satisfied informational in a context with constant variety than humans with higher cognitive complexity (e.g., physicians). The optimal incongruity level depends on the complexity of the cognitive structure.

We can conclude that in an *under-load situation* (I « 'individual optimum', see Figure 8) operators try to increase the complexity of their environment by different activities (see Table 3). If the sensory stimulation is too low and can not be increased in some other way (e.g., watching television or video), then operators tend to show locomotor exploration, manipulatory or investigatory behaviour (e.g., playing games). Task related actions, that could be classified as errors, are sometimes a subconscious, but a high rational strategy to increase external complexity.

Table 3 Survey of activities classified along the dimension of "response-complexity" (from Brown & Gregory 1968, 810-811)

1.) *Basic information-processing mechanisms*, e.g., mechanisms governing the transfer of information from short-term memory storage to more permanent storage and comparisons of percepts with short- or long-term memory or expectancies derived therefrom.
2.) The *orienting response*, which involves information-processing mechanisms *plus* motor and physiological components such as changes in heart rate.
3.) Relatively *prolonged direction* of the receptors toward a source of stimulation (e.g., looking, listening, touching), which very likely involves the preceding processes plus motivational components such as those frequently denoted by terms like curiosity, boredom, monotony, aesthetic pleasantness.
4.) *Locomotor exploration*, which again involves the preceding but includes in addition the active movement of the organism toward a source of stimulation.
5.) *Manipulatory* or *investigatory behaviour*, which includes as a further component the effecting of some sort of change in the environment.
6.) *Integrated sequences* of the above, e.g., play in young organisms and various forms of artistic enterprise.

We can conclude that in an *over-load situation* (I » 'individual optimum', see Figure 8) operators try to reduce their activities. The results of Moray and Rotenberg (1989, 1337) suggest "that operators prefer to work only one fault at a time and that this 'cognitive lock-up' hinders recognition of further faults."

9 CONSEQUENCES FOR THE DESIGN OF MAN-MACHINE SYSTEMS

Bainbridge (1982) describes very clearly the problems arising when an operator has to take over a complex process during a monitoring task (the vigilance problem). To take-over process control is especially problematic when the system runs into an unknown state. Training in a simulator is one possible consequence, better is permanent on-line control in the real process. High skilled operators tend to lose the potential to be aware of the whole process. They need a special qualification to get *open minded* (to increase the perceptual range).

If incongruity is too low, then humans try to increase the contextual complexity. This perspective allows us to have an alternative interpretation of human 'failures' in inescapable situations with information under-load (e.g., process monitoring in a steady-state). To increase the signal rate of the machine system artificially is not an appropriate design strategy for man-machine systems (Bainbridge 1982, 154). Job rotation and job enrichment can help to reduce information under-load, but not for a long time. Depending on the learning rate of the worker, we have to be aware of the monotony problematic.

The best solution is to involve the worker in the task solving process, especially when the task is a 'complete task' (Ulich et al 1991). Operators should have on-line control over the real process (Bainbridge 1982). Ulich (1983) formulated a global principle: differential and dynamic work design. There is no fixed 'one best way' for task solving processes. To satisfy the human need for variety (and optimal information) the work system must be flexible and customisable. Following Ulich's dynamic work design principle we have to increase continuously -- but not abrupt (as in alarm situations) -- the task and context variability over time. Of course, this demand leads to difficulties in complex system design. But, neglecting this demand we run directly into most of the ironies described by Bainbridge (1982).

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