An Anticipatory Searchlight Approach

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Abstract
Anticipatory Modelling and Computing (AMC) is identified as the key difference between Popper's Bucket Theory of Science (BTS) and his Searchlight Theory of Science (STS). In analysing relevant research about intelligence and knowledge, it is found that computer based AMC may be successfully applied in order to enhance human learning and knowledge handling according to the STS paradigm. A preliminary design of such an Anticipatory Searchlight Engine (ASE) is developed. It is based on an icosahedric fractal model. A computer implementation of ASE is proven quite straightforward and feasible. However, the current one needs additional elaboration.
Keywords: Anticipatory Modelling and Computing, Searchlight Theory of Science, Anticipatory Searchlight Engine, Icosahedric Fractal Infoset.

1 Introduction

Karl Popper (1979) has made a clear distinction between what he calls, '*the bucket theory of science' (BTS)*, and the '*searchlight theory of science' (STS)*. The former, BTS currently being the dominant paradigm but STS, according to Popper, being the more powerful and enabling one. The difference is illustrated in fig. 1. According to BTS, learning is just a question of filling the "bucket" with as many discrete knowledge elements as possible. As much as possible is the obvious goal of BTS.

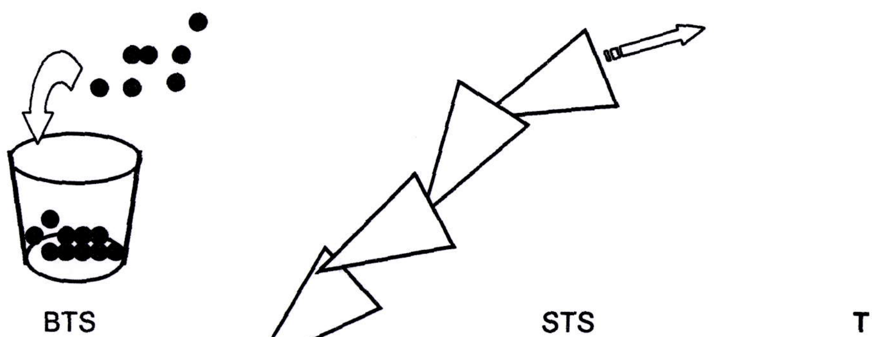

Figure 1: The Bucket (BTS) and the Searchlight (STS) Theory of Science.

The starting point of BTS being the assumption that before we can know or say anything about the world, we must have gathered perceptions or sense experiences. Hence, our experience or knowledge consists either of accumulated perceptions or otherwise of accumulated, sorted, and classified sense expressions. Because of this view, our mind works like a container - or a bucket – in which knowledge elements, as indicated in fig. 1, randomly accumulate during our lifetime. Another significant property is that BTS perceive knowledge as consisting of discrete and unrelated knowledge elements or facts.

According to STS, on the other hand, our hypotheses, expectations and theories precede the observations. With help of completed observations the hypothesis at hand may be tested, and, if necessary, modified. In fig. 1 those hypotheses are visualised as searchlights, which successively guide us further and further into the knowledge space. Learning becomes an infinite activity, but a new searchlight is guided and oriented not only by the preceding one, but even by its context and current expectations and objectives. With other words, important connections with anticipatory theory and anticipatory computing here emerge as obvious. In contrast to BTS, in STS knowledge is understood as a continuum with strong relations between the parts.

Hence, in STS observations seem to be planned and selective perceptions, which are guided by an anticipatory system. Consequently, the better our searchlight, the more useful and relevant our knowledge about the world will be. Here it is obvious that active anticipation may be seen as the key difference between a system learning according to BTS and STS respectively.

Hence, the purpose of this paper is to more thoroughly investigate the idea that learning according to STS can be seen as an anticipatory activity.

2 Challenges

There are at least two main challenges linked to the STS approach. First, accepting STS as a reasonable model for scientific knowledge creation or knowledge organisation, to what degree and in what way will it be possible to influence a shift from the dominating BTS paradigm towards a more effective STS one?

Second, with current technology and scientific insights at hand, to what degree will it be possible to enhance STS with help of a computerised support system? This support may be conceptualised as an Anticipatory Searchlight Engine (ASE) implementing an Anticipatory Inquiring System (AIS). With other words, can anticipatory modelling and computing (AMC) increase the effectiveness of our searchlight by helping and guiding us in our planning and preparing of new observations? My assumption here is that the answer to that second challenge is positive.

Accepting that last assumption, at least for the time being, the discussion in this paper will concentrate around the following main questions:

- Is a technical support of STS in form of an ASE feasible and possible?
- What functions can in that case ASE most suitably support us with?
- What does a reasonable robust and effective first tentative design of an ASE look like?

3 Knowledge for an Anticipatory Inquiring System

It is exciting to observe that Popper's discussion around STS has clear connections to several other theories of knowledge creation and knowledge organisation. Obvious examples are Inquiring Systems (Churchman, 1971), Constructivism (Piaget, 1937; le Moigne, 1994 and von Glasersfeld, 1998), Auto Organisation and Autopoiesis (Atlan, 1979; Maturana and Varela, 1980) and Fractal Intelligence (Dubois, 1990). Hence, as a base for the forthcoming ASE design, I will start with analysing some of those most stringent and promising research findings and hypotheses.

3.1 Constraints

The total knowledge space (K), i.e. all there is to know, may be a space with many dimensions ($\mathbf{R}^n$) and a complex topology. For our purpose here, however, it may be dichotomised into four two-dimensional fields according to fig. 2. Those are, (1) what you do not know that you know, i.e. unconscious knowledge, (2) what you know that you know, (3) what you know that you do not know, and (4) what you do not know that you do not know.

Here it has to be observed that knowledge is infinite, i.e. the fourth field, K4 in fig. 2, extends all the way into infinity, i.e. K has no outer boundary. Learning can here be seen as the activity of increasing area K2. In BTS this learning may be interpreted as a random walk into area K4. STS learning, on the other hand, is guided by a searchlight, or with other words, by an anticipatory system.

K4	K1	K2	K3	K4
Not know Not know	Not know know	Know know	Know not know	Not know Not know

Figure 2: The four different regions K1 to K4 of the total knowledge space K.

Fig. 2 can be used as an illustration of Simon's (1995) analysis of our bounded rationality. He points out that our rationality, i.e. our knowledge, is critically bounded in at least three different ways. First, we know just an infinitesimal part of all that there is to know. Hence, the small fraction we know put in relation to the total knowledge space can be expressed as in eq. 1. With other words, independently of how much we as individuals happens to know, in relation to the total knowledge space our individual knowledge quotient will always be zero. One way of ameliorating this sad situation may be to successfully combine the K2 of several individuals.

The second restriction concerns our bounded capacity for computing, i.e. we arrive to compute just a few of all the innumerable implications of the things we, after all, happens to know. Even this is a severe restriction as the very heart of creation or design is the finding or invention of new and creative combinations of things we already know.

$$K2 / (K1 + K2 + K3 + K4) = K2 / K = K2 / \infty = 0 \tag{1}$$

K1, unconscious knowledge
K2, conscious knowledge
K3, conscious unawareness
K4, unconscious unawareness
K1 + .. + K4, total knowledge space, K

The third restriction at last is the fact that also our attention has a very low capacity. "The Magical Number Seven" is often used as a metaphor for how many knowledge "chunks" we can keep in short-term memory, i.e. the memory of attention. Here it is also important to observe that a knowledge element can only be transferred from long to short term memory if it is recognised and if it is indexed.

Further, even if it is not part of Simon's discussion we obviously also are restricted by a rather narrow bandwidth. This means that we are able to increase K2 with just a finite and limited number of knowledge units, or bits, per time unit. Because of the Bremermann limit of 10^{93} (Bremermann, 1962) this dire fact will become equally true whatever computer support we may apply. In fact, this transcomputational problem is a neat and very striking demonstration that a BTS approach will never work.

However, Winograd and Flores (1986) have already demonstrated that the computer has its strong properties there the human being is restricted and vice versa. Hence, there still is a hope that an insightfully designed Man-Machine system could help in both better organising our current knowledge and effectively guiding us in learning the right new things at the appropriate moment.

3.2 Anticipatory Learning

According to STS (Popper, 1979), the first step in learning is hypothesis creation. After that follows observations, i.e. planned and prepared perceptions, in order to test the hypothesis. Hence, the hypothesis may pass the test, at least for the time being, or it may be falsified. In the latter case, a new or modified hypothesis has to be formulated.

Here it is interesting to see that both Nadin (2000) and van de Vijver (1998) have proposed an enlarged definition of anticipation. This means, an anticipation not only along the time dimension, but more seen as an infinitely enfolding co-relation, or an anticipation with a flattening of time. Clearly this enlarged type of anticipation fits very well into Popper's creation of new hypotheses. Hence, anticipation evidently may play a fundamental role in STS.

3.3 The Brain as a Dynamic Map

There seems to be a mutual relationship between the brain and its organisation, and the outer reality (Piaget, 1937; Dubois, 1990; von Glasersfeld, 1999; Holmberg, 2000). However, this may not be conceived as a fix or static model. Contrary, the brain is continuously reorganising itself in creating new knowledge structures.

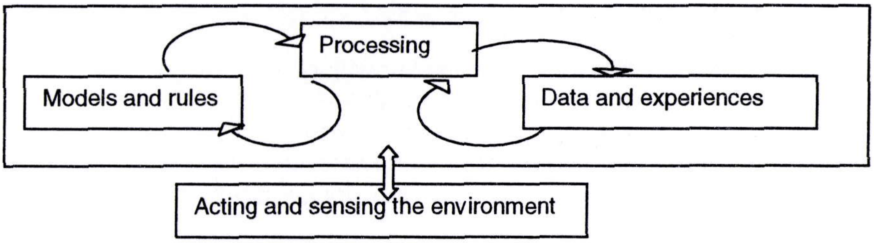

Figure 3: Main brain processes.

Those structures can be seen as new hypotheses to be tested. Here the next conclusion will be that it is impossible to learn in isolation. It is necessary to have direct access to a reality in order to continuously test and verify, or refute, those new hypotheses. Hence, the brain, or its organisation, makes it possible to interact with the reality and those interactions and observations, in their turn, will trig further remodelling and reorganisation of the brain.

Dubois (1990) has elaborated those ideas in more detail. Hence, intelligence may be seen as an auto organising function, which develops itself. Consequently, an intelligent system (living or non living) is in continuous advancement and increases at the same time its complexity. Criteria for such an intelligent system are that it is inventive and creative. That it can adapt and find new behaviours in order to meet new and unknown situations. At last, it is capable of memorising earlier experiences.

It is also stated (Dubois, 1990) that an intelligent system must auto-learn (unsolicited learning) and that it must have a function of auto-meta-learning, i.e. it has to reflect on its own methods for learning. Further, Dubois (1990) puts forward the hypothesis that the brain has a fractal organisation or structure. In this way we will have a recurrent, or auto-replicate, and hierarchic brain structure.

Dubois (1990) also says that intelligence is related to a goal. That goal is to create a better or more useful representation of the environment and the system itself. In this way it will be possible to better handle arriving situations. Even here, we can se a clear parallel with STS's ambition to timely learn just what we need. At last, the brain is not only storing information. It is also storing rules for the processing of that information. Hence, the brain content is continuously changing. New representations emerge and old ones are changed or forgotten. Those processes can be conceptualised as in fig. 3.

3.4 Knowledge as a Repertoire for Action

Ashby (1958) has formulated the law of requisite variety (LRV) stating that an effective controller must have at least as great a variety as the system to be controlled. That law can also be taken as a paradigm for knowledge and knowledge acquisition according to fig. 4. Here, R is an individual's total repertoire of feasible actions in response to the environment's set of potential challenges, C. Satisfactory knowledge is to dispose of an action with acceptable outcome (o) for each thinkable challenge.

R

		a1 a2 .... am
C	c1	O11 O12....O1m
	c2	O21
	.	.
	.	.
	cn	On1...........Onm

Figure 4: Outputs, O11...Onm, of a repertoire of actions a1 ..am to be considered in response to a set of potential challenges c1..cn coming from the environment.

Learning here corresponds to expanding the repertoire, i.e. in adding yet another column to the CR-matrix. Further, according to LRV, more columns in the matrix will increase the possibility of finding an action with a satisfactory outcome, O. However, before an action has been applied for the first time it merely can be seen as a hypothesis, that still has to be tested and verified. After the first application, on the other hand, the outcome is known and the column in question will be kept or dropped according to the system's utility of that outcome. Consequently, the CR-matrix will never be a static structure. Columns will be added and dropped all the time. Even rows may be added if the system moves itself into a more complex environment.

Anyhow, according to LRV, in order to ensure an action (a) with an acceptable outcome (o) in response to every possible challenge (c), the number of available actions must at all times be greater than the number of potential challenges.

3.5 Operational closeness

Varela and Maturana, as explained for example in (Maturana and Varela, 1980; Varela,1980; Mingers, 1995), have developed and elaborated the ideas of autopoiesis, or self-producing systems, and organisational closeness. Autopoietic systems can be defined as self-producing systems, i.e. their components participate in producing themselves. This property may even be accounted for the difference between living and nonliving systems.

Further, with autopoiesis follows several interesting implications (Mingers, 1995). For example, autopoietic systems are organisationally closed. This does not mean that the system is isolated from its environment, but it denotes that its organisation and identity is not given primarily through its input and output. The autopoietic systems are also structurally determined. This means that the changes that a system undergoes are determined, instant by instant, by its internal structure. Input from the environment can only act as a trigger, it can never determine structural changes in the system. Those are merely a compensation for the interaction. For Varela (1980) this constitutes the key difference between a Command paradigm and one of Autonomy. Obviously, even this are insights, which are well in line with the STS paradigm.

In contrast to many others, Maturana and Varela (1980) have always been very explicit on the philosophical implications of their work. In line with that stance, they have openly argued for a constructivist epistemology. Constructivism (von Glasersfeld,1984, 1998; le Moigne, 1994, 1995) being a scientific epistemology stating that our experiences or interpretations of the world are essentially constructed by ourselves. Realism or logical positivism, on the other hand, is the dominating epistemology in our current society. It is opposing constructivism in stating that there exists an objective, independent real world. A world that we can directly sense and learn about.

Churchman (1971) has argued that any inquiring or knowledge building system inevitably and unconsciously builds upon a philosophical and epistemological base. Here it is evident that BTS is more closely related to realism and logical positivism while STS is more easily combined with a constructivist epistemology.

3.6 Learning as a Cyclic activity

In his "la Méthode", Morin (1977) argues that learning is not a question of memorising "everything" in an accumulative or encyclopaedic meaning. Contrary, it is an issue of identifying strategic links between apparently disjoint fields and of finding the crucial relations in disorganised areas. Learning becomes a cyclic activity that never comes to an end. Morin's organising principle hence becomes an issue of articulating the disjoint and of complexifying the simplified.

That learning in Morin's sense will increase our repertoire (R) for actions according to eq. 2. The alternatives evidently are stagnation or retardation according to eqs. 3 and 4 respectively. Further, to the degree the learning is guided by anticipation it can be described by eq. 5, compared with a random, or perception (p) based, learning according to eq. 6. Hence, even here we find clear evidences for STS supported by anticipatory learning.

Learning:	$R(t+1) > R(t)$	(2)
Stagnation:	$R(t+1) = R(t)$	(3)
Retardation:	$R(t+1) < R(t)$	(4)
Anticipatory (STS) learning:	$R(t+1) = f[R(t), R(t+1), \ldots]$	(5)
Random (BTS) learning:	$R(t+1) = f[R(t) + p(t)]$	(6)

3.7 Thrownness and Computer Support

Winograd and Flores (1986) make many striking reflections concerning a possible and feasible computer support. Firstly however, they emphasise the unavoidable "thrownness" in all interaction with an environment. In short, we can not avoid from acting in any situation, but all our actions have to be based on unstable and tentative representations. Hence, it will be unavoidable to make mistakes but with better anticipation and better hypotheses we may hope that those mistakes will be less grave and that they will provide better learning. Van de Vijver (1998) designates this as "*failing better*".

Further, according to Winograd and Flores (1986) information is not only something instrumental that transfers facts and instructions between people. It is more importantly something used to build mutual understandings and commitments among them. At last, computers may be of best help if we apply the strategy of building synergetic man-machine systems instead of trying to replace man with a computer.

Some last comments concerning knowledge space and learning may here be in place. Firstly, Popper (1979) makes a distinction between world one, two, and three. The first one being the outer real world, the two others being the knowledge held in people's collective minds and knowledge stored in libraries and databases of different forms respectively. The net and other modern technology has drastically increased our access to the information stored in libraries and databases but it has done nothing to the living knowledge in our minds. However, only knowledge in our minds can be used in creating no ideas and hypothesis or for trigging actions. Hence, this may be a crucial difference between support given by current technology and the forthcoming ASE.

Further, evidently there is a great difference between the knowledge hold by any individual person and by the community of all living people, see eq. 7. Hence, it could be a profitable strategy trying to increase and ameliorate the communication and collaboration between people. This is well in line with Winograd and Flores (1986) stressing of the importance of building commitments. On this point, on the other hand, already current technology has proven itself of being very useful. Hence, those communicating facilities ought to be integrated into ASE.

Individual knowledge (KW2i) compared to collective knowledge (KW2c)

$$KW2i \ll KW2c \qquad (7)$$

3.8 The Icosahedra Infoset as an Organising Principle

Stafford Beer (1994) has defined the *Team Syntegrity* protocol, or method, as an optimal way of putting the collective knowledge and creativity of a group of people, the infoset, into prosperous work.

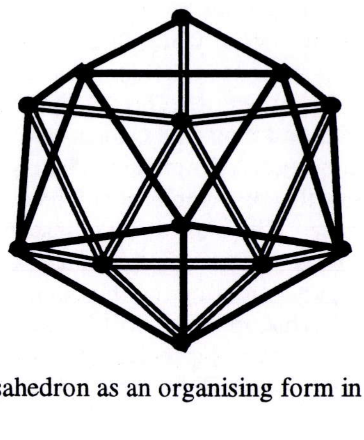

Figure 5: The icosahedron as an organising form in Team Syntegrity

The icosahedron, a regular polyhedron with twelve vertices, twenty faces, and thirty edges, see fig. 5, forms the basic metaphor for the organisation of the infoset and the Team Syntegrity's working protocol. Team syntegrity builds on basic work of Buckminster Fuller (1979), who already in 1948 used the icosahedron and the tensegrity principle for forming building structures.

The main ideas in Team Syntegrity are to provide an as democratic organisation as possible and to avoid pre-set agendas. Further, to optimise the information interchanges and flows of information between the participators in the Infoset. The procedure has proven to be extremely robust, intuitive, and effective (Holmberg, 1997).

3.7 The Real World is a Quantum World

Milburne (1998) has discussed quantum computing in light of the so called Feynman Processor and the Church-Turing principle, which says, "*Every finitely realisable physical system can be perfectly simulated by a universal model computing machine operating by finite means*". Further, Millburne, argues that if computational systems are a natural consequence of physical law, then a quantum computer is not only possible but inevitable. Hence, it may take decades or more, but a viable quantum computer is a certainty. This will, among many other things, drastically improve the pace of testing and verifying new hypotheses. Our ability to create knowledge about the world will increase with a quantum leap. Hence, in discussing an ASE and its possible properties and capabilities we may not let us be restricted by current computer technology.

4 Synthesis for an Anticipatory Searchlight Engine

As seen in the previous section and in fig. 6, there are a lot of powerful and interesting ideas and research findings with connotations to our task. Consequently, the main problem is not so much to identify and retrieve such information but more to make a useful combination of it. The endeavour here will hence be to make such a synthesis, i.e., a combination of prevailing knowledge that can work as a launching platform for the forthcoming design of the Anticipatory Searchlight Engine (ASE), see fig. 6.

At first anyhow, it is important to conclude that most of the research findings discussed seem to support STS. Further, it seems feasible supporting STS with an ASE.

From what has already been said it may be evident that the computer will not be able to help us acquire significantly more information. The equation 1 will always be true. Further, the computer alone will not be able of producing new knowledge. Hence, a replacement strategy is abolished. The main strategy instead, will be to implement ASE as a Human-Computer symbiosis. In this way ASE may be seen as a Human-Computer system in which the human part is reinforcing the computer and the computer part is strengthen by the human one. This approach will be well in line with Stock's (1993) Metaman, i.e., a new superior man, supported by and inseparable integrated with supporting computer technology. This will be achieved along the following main lines.

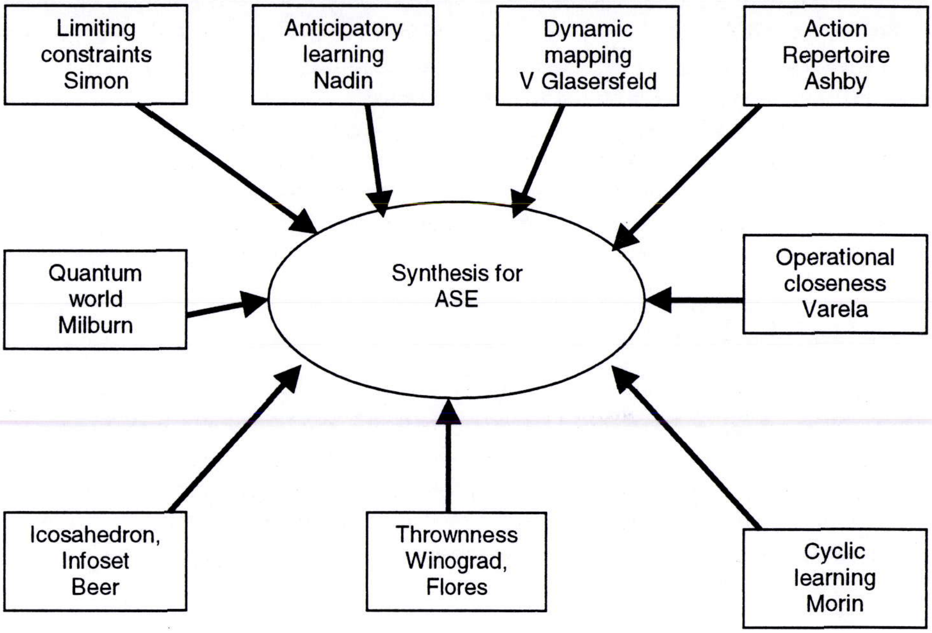

Figure 6: Some research findings supporting the ASE concept.

Hence, AES will implement five main functions according to table 1. At first, ASE can help us creating new hypotheses by making new combinations of the knowledge we already dispose of. This is the first and most crucial step in the knowledge process set out by the STS. To the degree that an anticipatory process may guide that combination, as discussed for example by Nadin (2000), instead of being entirely random, the approach will gain in effectiveness.

Secondly, ASE may also help us widen our narrow focus of attention. In this way more things may be taken into account at the same time. This may require some sort of improved visualisation tool as discussed for example by Simon (1995).

A third aid ASE can give us concerns computability. Hence, with ASE we may be able to compute more implications of alternative or hypothetical decisions and courses of action. This improved ability will sharpen our hypothesis testing skills in a desirable manner.

Table 1: Main functions of AES.

1. Assist in creating hypotheses
2. Assist in widening and directing focus of attention
3. Assist in calculating implications
4. Assist in indexing, recognition and information retrieval
5. Assist in decreasing our thrownness

Further, ASE may also help us in retrieving the necessary information for a given task. This includes indexing systems but also, and more importantly, pattern recognition and identification of necessary data and facts. Once the information is identified, it may be retrieved from any source, both internal and external.

At last, the inevitable thrownness situation (Winograd and Flores, 1986) may be discharged if an anticipatory system can tell us in advance what situations to expect. With such a support it would be possible to prepare oneself to a certain degree, for example by testing different courses of action in advance.

5 Tentative AES Design

The Anticipatory Searchlight Engine (ASE), i.e. the computer part of a forthcoming synergetic man-machine knowledge booster, will be implemented in an ordinary personal computer environment. The preliminary or tentative design of ASE, release 0, that is given here is the pragmatic conclusion of the analysis and synthesis, which has already been discussed earlier in this paper. The design is open ended and living, i. e., it will be modified and refined as new experiences and lessons are gained from implementation efforts and prototyping experiments.

5.1 Design of ASE-0

Stafford Beer's (1994) icosahedrically organised infoset, see fig. 5, is tentatively taken as the basic knowledge organiser in ASE. Hence, each of the twelve vertices of the regular icosahedron (RI) represents a knowledge entity, or a knowledge cluster, and each of the thirty edges represents a relation, or relation vector, between two such knowledge entities. Due to the RI:s organisation it will be no special ordering or priority between the elements in the structure. Further, the RI has fractal and recursive organisation as each vertex may contain a whole RI on the next lower level. In the other direction, the RI in focus is contained in a vertex of the RI on the next higher level. An individual vertex in the total knowledge structure will hence be fully identified by three co-ordinates denoting, vertex of RI in focus, level of parent RI, and vertex in parent RI.

Given the knowledge structure based on the RI, the next dominant feature is that the whole structure is dynamic. This means that it continuously re-organises itself and knowledge entities are moved up, down, or sidewise to new vertices. In this way new and interesting combinations or knowledge patterns may emerge.

A third main feature is the display and interaction function. Here it will be possible to see the RI in perspective but also as a plane figure with preserved topology. By using colours in a similar way as Beer (1994) it will be possible to highlight certain features and properties. With the interaction function it is possible to turn around the RI or to move between vertices or to shift vertex (subject) or edge (relation) in focus. It is, of course, also possible to move up or down between different levels in the fractal knowledge structure.

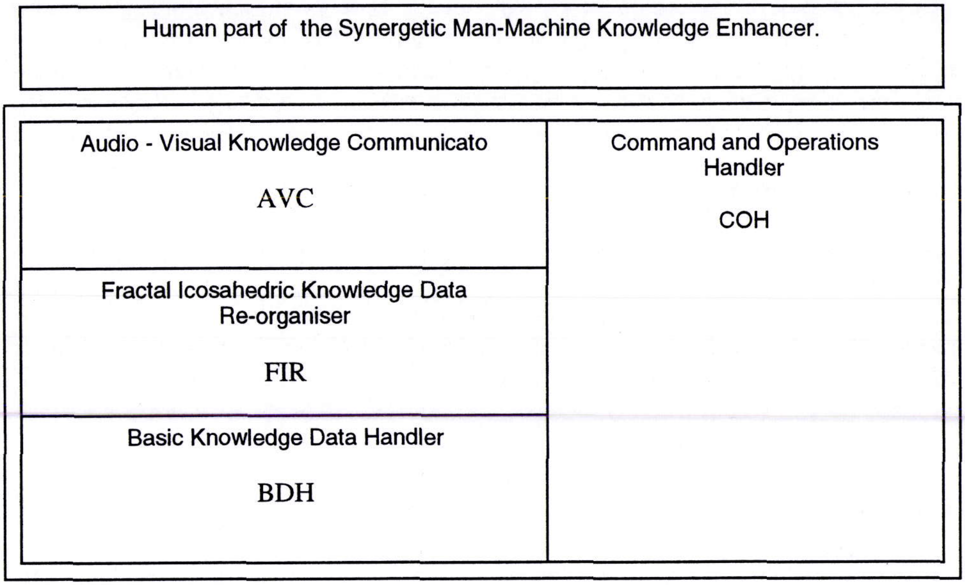

Figure 7: Basic modules in the ASE design

The first tentative AES design contains four main modules according to fig. 7. The user, i.e. the human part in the synergetic man-machine knowledge enhancer, operates the system via the Commands and Operations Handler (OCH). Via OCH different commands and necessary data are entered and system messages and prompts are displayed. This module is implemented according to currently accepted rules for graphical user interfaces and computer – user interaction.

The Basic Knowledge Data Handler (BKH) supports a conventional rational data base with basic knowledge elements. A basic knowledge element can in this context be nearly anything that the user decides to have accessible. It can be stored in the local base but it can also be a reference to an external source, for example on the web. There are no predefined concepts or categories in this database but the user may define any relations between stored entities. All such relations, however, are fuzzy relations. With each stored item there are also a counter and a time stamp. Hence, it is possible to see when and how often an item has been accessed.

In the Fractal Icosahedric Knowledge Data Re-organiser (FIR) the items in BKH are allotted positions in the fractal RI structure. This process is partly random and partly guided by the items' access rates. However, the user may at any moment change the exact rules for this allocation process. This process is also going on all the time. This means that the structure is dynamic and no item may be locked to a certain position in the RI structure for very long.

The last module is the Audio-Visual Knowledge Data Communicator (AVC). This unit is responsible of presenting the current configuration of the knowledge structure. The basic presentation unit is the regular icosahedron, both in plane and three-dimensional form. This, however, can be complemented with several other data formats.

5.2 Implementation of ASE-0

ASE, or at least its first prototype ASE-0, is supposed to be implemented on an ordinary personal computer. The necessary software will be produced with help of a commercial, so-called "*Rapid Application Development*" package. Hence, the implementation of the design is foreseen to be reasonable straightforward and swift from a purely computational point of view. First experiences also support that assumption.

6 Conclusions

Popper's Searchlight Theory of Science (STS) is underpinned by striking and convincing research findings of several other eminent scholars. Hence, it seems reasonable to take STS as a base for any prosperous knowledge creation activity. Further, as the human rationality obviously is severely bounded in areas there the computer has its most superior properties; it appears straightforward trying to combine the human and the computer into a synergetic man-machine system.

Hence such a system, an Anticipatory Searchlight Engine (ASE), at first has to enlarge our limited focus of attention. Further, ASE will also help us compute new combinations by continuously forming new relations between items in our knowledge bank. Anticipatory theory, in its enlarged sense, in combination with Beer's icosahedric infoset has proved itself being a promising base in the design of such an device.

Anticipation may seem to play a minor role in ASE. Here, however, it is important to remember that any intelligent behaviour has to be seen in relation to an objective or a goal. Hence, the anticipatory character of ASE will emerge fully first if it is applied in a real case. Given, for example, that we want to investigate a subject area. That goal will then work as a searchlight for the ASE according to the principles of Exploratory or Evolutionary Anticipation (Holmberg, 2000).

The strength of the ASE-approach, at last, will be further tested in forthcoming experimental prototyping.

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