
The Self-Organization of Distributed Cognition: a connectionist approach

Research Proposal for a “Geconcerteerde Onderzoeksactie”,
submitted to the Research Council of the VUB by

Francis Heylighen & Frank Van Overwalle

Contents

Summary	3
Preface	4
1. Presentation of the research team	5
1.1. Collaboration between the groups	5
1.2. Members of the team	5
1.3. Short biographies of the team members	7
2. Activities and achievements of the research team	10
2.1. Previous research	10
2.2. Teaching	11
2.3. PhD’s delivered	11
2.4. Organization of conferences	11
2.5. Contacts and collaborations	12
3. Introduction to the research theme	13
3.1. A connectionist perspective on cognition	13
3.2. Cognition at the social level	14
3.3. Empirical studies of social cognition	15
3.4. The extended mind	15
4. Aim: towards an integrated theory of distributed cognition	16
5. Social relevance and potential applications	17
6. Basic assumptions	18
6.1. Groups of agents self-organize	18
6.2. The organization co-opts external media for information exchange	20
6.3. Distributed cognitive systems function like connectionist networks	20
6.4. Information in the network is propagated selectively	21
6.5. Novel knowledge emerges	22
7. Methodologies for distributed cognition research	23
7.1. Theoretical investigation	24
7.2. Computer simulation	24
7.3. Observation	25
7.4. Group Communication Experiments	26
7.5. Computer-mediated games	27

8. Concrete subprojects	27
8.1. Groups of agents self-organize	27
8.2. The organization co-opts external media for information sharing	30
8.3. distributed cognitive systems function like connectionist networks	32
8.4. information in the network is propagated selectively	35
8.5. novel knowledge emerges	38
9. Deliverables	40
9.1. Publications	40
9.2. Simulation environments	40
9.3. Empirical data	41
9.4. Workshops, conferences and lectures	41
10. Project planning	41
Year 1: 2006	41
Year 2: 2007	41
Year 3: 2008	42
Year 4: 2009	42
Year 5: 2010	42
Requested Funding	43
Relevant publications of the research team	44
Bibliography (publications by others)	49

Summary

This research project is proposed by a multidisciplinary team led by F. Heylighen and F. Van Overwalle. Its members have expertise in cognitive science, psychology, AI, philosophy, economics, political science, law and linguistics, and advanced research experience in connectionist simulation, complex systems, self-organization, and group experiments.

The project aims to develop an integrated theory of the self-organization of distributed cognition. Distributed cognition is seen as the confluence of collective intelligence, and “situatedness” or the extension of cognitive processes into the physical environment. It concerns the information processing and learning that occurs on the social level, by the propagation of information from agent to agent across media. The theory we wish to develop would have a wide range of social and technological applications, including: better understanding of socio-economic development and diffusion of information, control of cognitive biases and social prejudices, knowledge management and organizational learning, and the development of an intelligent, “semantic” web.

Our approach is based on five basic assumptions inspired by earlier research: 1) groups of agents self-organize to form a coordinated system, 2) the system co-opts external media for transmission of information, 3) the resulting distributed cognitive system can be modelled as a connectionist network, 4) information in the network is propagated selectively, 5) novel knowledge emerges through non-linear, distributed processes. These hypotheses will be elaborated and tested using a combination of theoretical modelling, computer simulation with multi-agent systems and recurrent connectionist networks, and empirical observation, both in controlled laboratory experiments with groups and open-ended observation of “real-world” processes.

Preface

The following is a research proposal, submitted to the GOA ("Geconcerteerde Onderzoeksacties") funding program of the Vrije Universiteit Brussel (VUB), in the category social sciences and humanities ("humane wetenschappen"). A GOA project is intended to further support and stimulate the activities of an experienced VUB research group, lifting it to the level of a "center of excellence". As such, the funding can be seen as complementary to the funding that the team already has collected for individual collaborators and more specific projects, allowing it to fill in the gaps and develop a more long-term, integrated research strategy.

The present proposal should be seen as a project for the research group as whole, i.e. both the people to be funded by GOA money and the people already funded via other channels. As such, it is much more wide-ranging and ambitious than what could be expected on the basis of the GOA money alone. Our intention is to show that this additional money will help us to grow to an "excellence" level by providing the necessary stability, security and continuity, making us less dependent on smaller-scale and shorter-term contracts.

It is precisely because of this hoped-for continuity that we can realistically afford to be ambitious: our previous record has convinced us that our team has the necessary experience, expertise and creativity to tackle the different problems in our domain. We are therefore confident that as a team we will be able to achieve most of the goals listed in this proposal. Of course, since the results of research are by definition unpredictable, some of our subprojects may prove unfruitful, and therefore may have to be abandoned. But we are equally likely to discover promising avenues not yet envisaged here, and perhaps achieve unforeseen successes.

The present proposal is a reworked version of a GOA project that was submitted one year ago, but not funded. Although the referees appreciated both the project and the expertise of the group, they raised a number of questions about the approach, in particular noting that the project appeared too ambitious. It is in part to clarify that issue that we added the present preface. We have tried to address the other concerns in the rest of the proposal, by further extending and clarifying our assumptions and methods.

Compared to a year ago, our general understanding of the problem domain has significantly advanced, especially with respect to the networked or connectionist nature of distributed systems, the "trust-based" nature of their connections, and the essential role of self-organization. This should give us a more coherent picture of the domain as a whole.

Another major change is that one of the two collaborating research teams, the *Evolution, Complexity and Cognition* group, has about doubled in size, attracting several promising new researchers, both funded and not funded, who brought in a lot of fresh ideas and competencies. (This has led the group to apply for official recognition as an independent VUB research center, rather than as a subgroup of the Center Leo Apostel.)

We believe that these changes further strengthen our capability to realize our research objectives.

1. Presentation of the research team

In the following, the names of the members of the team are printed in **bold** for easy reference. The present proposal is an initiative of Francis **Heylighen** and Frank **Van Overwalle**, supported by their PhD students, PostDocs and research assistants. As such, the research team is a collaboration between two groups, the interdisciplinary *Evolution, Complexity and Cognition* group (ECCO), led by **Heylighen**, and the *Social Cognition Lab* (SCL), led by **Van Overwalle**, which is part of the *Personality and Social Psychology* department (PESP). The two groups have built up complementary expertise concerning distributed cognition: ECCO mostly in transdisciplinary, theoretical frameworks and multi-agent simulations; SCL in experimental psychology and connectionist simulations.

For an overview of their activities, check their respective websites:

- <http://pcp.vub.ac.be/ECCO/>
- <http://www.vub.ac.be/PESP/VanOverwalle.html>.

1.1. Collaboration between the groups

ECCO and SCL have been collaborating since 1990 on the dynamics of cognition, with special focus on causal attribution, connectionist learning, and the development of shared or collective knowledge. This resulted in several co-authored publications, including [**Van Overwalle & Heylighen**, 1991, 1995; **Van Overwalle, Heylighen et al.**, 1992; **Bollen, Heylighen & Van Rooy**, 1998; **Heylighen, Heath & Van Overwalle**, 2004; **Van Overwalle, Heylighen & Heath**, 2005].

Heylighen and **Van Overwalle** were moreover co-promoters of a PhD dissertation [**Bollen**, 2001], and have jointly submitted several research proposals, including the following :

- Evolutionary Construction of Knowledge Systems (main promotor F. **Heylighen**, funded FWO 1994-1999)
- The Social Construction of Shared Concepts: empirical study and computer simulation of a distributed cognitive process (main promotor F. **Heylighen**, funded FWO 2004-2007)
- Understanding Implicit Learning (main promotor Eric Soetens, submitted GOA 1998)
- Collective Knowledge Development (promotor F. **Heylighen**, submitted FWO 1999)
- Misperception about Groups by Groups (main promotor F. **Van Overwalle**, submitted FWO 2004)
- Mediated Evolution of Social Organisation: a multi-agent simulation (main promotor F. **Heylighen**, submitted FWO 2004)
- Development, simulation and test of a connectionist model of learning organizations (main promotor F. **Heylighen**, submitted FWO 2005)

1.2. Members of the team

The following is a list of the members of the two groups who will participate in this project, approximately in the order of when they first joined the team. The members will contribute to those parts of the research project that best match their interest and expertise (as summarized in the next section with biographies).

In practice, if this proposal would be accepted, the available GOA funding would allow us to employ 3 to 4 additional researchers over a 5-year period (2006-2010). These would join a team of some 10 people who are already funded, e.g. by the VUB as professors or research and teaching assistants, and by outside sources such as the Flemish government (FWO), European Commission, or US government.

As is current in academic institutions, the funding for non-tenured researchers is quite variable as short-term research contracts end, and may or may not be renewed or replaced by different contracts. This depends on various contingencies that have little to do with our long-term research strategy. Therefore, it is difficult to state with any certainty for which individuals the funding we receive would be used, although the first priority will be to support the team members that are presently listed as not funded. But as some of these people may find funding elsewhere, we may decide to use the money to support presently funded members whose contract has ended, or promising new people who have impressed us with their competence and motivation.

Presently funded:

- Prof. Dr. Francis **Heylighen** (promotor, ECCO)
- Prof. Dr. Frank **Van Overwalle** (co-promotor, SCL)
- Dr. Bertin **Martens** (researcher European Commission, ECCO)
- Carlos **Gershenson** (researcher FWO, ECCO)
- Bert **Timmermans** (researcher FWO, SCL)
- Margeret **Heath** (researcher FWO, SCL)
- Marijke **Van Duynslaeger** (researcher FWO, SCL)
- Klaas **Chielens** (researcher OZR, ECCO)
- Mixel **Kiemen** (researcher DISC, ECCO)
- Marko **Rodriguez** (researcher GAANN, ECCO)
- Nick **Deschacht** (teaching assistant VUB, ECCO)

Looking for funding:

- Laetitia **De Jaegher** (PhD student, ECCO)
- Erden **Göktepe** (PhD student, ECCO)
- Dirk **Bollen** (PhD student, ECCO)

Former members:

These are group members who have left our local center at the VUB, but with whom we remain in contact and who may still contribute to certain parts of the project.

- Dr. Johan **Bollen** (associate professor, Computer Science Dept., Old Dominion University (USA), ECCO)
- Dr. Dirk **Van Rooy** (lecturer, Psychology Dept., Keele University (UK), SCL)
- Tim **Vanhooissen** (former researcher OZR, SCL)
- Andreas **Loengarov** (researcher, Computer Science Dep., University of Paisley (UK), ECCO)

1.3. Short biographies of the team members

Francis **Heylighen** is a research professor affiliated with the *Department of Philosophy* and the interdisciplinary *Center Leo Apostel*, and director of the *Evolution, Complexity and Cognition* group at the *Vrije Universiteit Brussel*. He has worked during most of his career for the *Fund for Scientific Research-Flanders* (FWO), first as research assistant (“aspirant”), then PostDoc, and finally tenured Senior Research Associate (“onderzoeksleider”). He received his MSc in mathematical physics in 1982, and defended his PhD in 1987, on the cognitive processes and structures underlying physical theories [Heylighen, 1990]. He then shifted his research to the self-organization and evolution of complex, cognitive systems, which he approaches from a cybernetic perspective.

Francis **Heylighen** has authored over 90 scientific publications, in a wide variety of disciplines, including a monograph and four edited books. Since 1990 he is an editor of the *Principia Cybernetica Project*, an international organization devoted to the computer-supported, collaborative development of an interdisciplinary knowledge network. He created (and still administers) the project’s website [Heylighen, Joslyn & Turchin, 2004] in 1993, as one of the first complex, interactive webs in the world. Since 1996 he chairs the *Global Brain Group*, an international discussion forum reflecting on the emerging information society. He is the present editor-in-chief of the *Journal of Memetics: Evolutionary models of information transmission*, which he co-founded in 1996, and member of the editorial boards of the *Journal of Happiness Studies*, and the journals *Informatica* and *Entropy*.

His work has received a wide and growing international recognition from peers, students and the general public. This is shown by such indicators as the number of references to his work in the *Web of Science Citation Index* (more than 200), on the world-wide web (about 16000 according to www.google.com), and in the national and international media (articles about his work have appeared among others in *New Scientist*, *Frankfurter Allgemeine Zeitung*, *Die Zeit*, *Le Monde*, the *Washington Post*, and *Knack*). This recognition is confirmed by the number of people that have applied to do PhD or PostDoc research under his supervision (several dozen from all around the world), and the invitations he regularly gets to lecture in different countries or to write review articles for leading reference works [e.g. Heylighen, 2002; Heylighen & Joslyn, 1995, 2001]. He is a Fellow of the *World Academy of Art and Science*, and his biography is listed in *Who’s Who in the World* and other international directories.

Frank **Van Overwalle** is a full professor affiliated with the *Department of Psychology* at the *Vrije Universiteit Brussel*. He has worked first as research assistant in the VUB department for new media and computer technology in education, then as PostDoc at the *University of California at Los Angeles* (1988-1989), and finally as PostDoc and tenured professor at the VUB psychology department.

He got his MSc in psychology in 1980, and defended his PhD in 1987 on “Causes of success and failure of freshmen at university: An attributional approach”, for which he received the *Tobie Jonckheere Award* of the *Belgian Royal Academy of Sciences, Letters and Arts*. He continued to work on attribution and social cognition, and then applied his and others’ research to the development of artificial neural network models of social cognition. He has received several grants from his university and the *Fund for Scientific Research-Flanders* in order to test some unique predictions derived from these theoretical proposals. This enabled him to employ several PhD students in his social cognition lab, who generate scientific output either as a PhD or in empirically oriented articles.

Frank **Van Overwalle** has authored some 40 peer-refereed scientific publications, in the domain of social cognition. His recent research focuses on artificial neural network models of various phenomena in the domain of social

cognition at large, to demonstrate the common cognitive processes underlying many social findings. The aim is to abolish ad-hoc hypothesis building which is currently very flourishing in social psychology, and to attempt to develop a general cognitive theory encompassing the whole of social psychology, in line with general theories of psychological information processing. This has resulted in a number of publications in top-ranking journals such as *Psychological Review* and *Personality and Social Psychology Review* with an impact score (SSCI) between 3 and 7.

His work is receiving a broad and growing international recognition from peers, as evidenced by some 200 references to his work in the *Web of Science Citation Index*. He is a member of the *Royal Flemish Academy of Art and Science's* committee of Psychology, the *American Psychological Association*, and the executive board of the *Belgian Federation of Psychologists* (BFP). He is a past secretary-general and president of the *Belgian Society of Psychology* (BVP), and is in the editorial board of the *European Journal of Social Psychology* and *Psychologica Belgica*.

Bertin **Martens** is an economist with a MSc (1979) from the *Katholieke Universiteit Leuven*. Since 1989 he works at the *European Commission* in Brussels on project design and evaluation, macro-economic modelling and implementation of structural reform programmes. He has combined his professional career with academic research by working part-time and taking sabbaticals to visit research institutes around the world. As such, he held Visiting Fellow positions at the *University of New South Wales*, the *Max Planck Institute for Research into Economic Systems*, *George Mason University*, and *Stanford University*—where he worked for six months with the Nobel Prize winner Douglas North. He focuses on cognitive science approaches to economic development and institutional change. In May 2004, he defended his PhD thesis [**Martens**, 2005] on the role of distributed knowledge in social and economic evolution, with F. **Heylighen** and M. Despontin as promoters. It will be published as a book by Cambridge University Press.

Carlos **Gershenson** is a computer scientist with a BEng (2001) from the *Fundación A. Rosenblueth* in México, and a MSc (2002) from the *School of Cognitive and Computer Sciences* at the *University of Sussex*. He is making a PhD on the design and control of self-organizing systems under the supervision of **Heylighen**. His research interests include distributed cognition, philosophy of mind, complex systems, artificial societies and computer simulation. At the age of 26, he already had published over 25 scientific papers in international proceedings and journals. He is a contributing editor to *Complexity Digest* and Book Review Editor of the top-ranking journal *Artificial Life*. His research has been covered in the national and international media, including *Nature News*, *Trends*, and *Technology Research News*.

Bert **Timmermans** is a psychologist with a MSc (1998) from the *Vrije Universiteit Brussel* and an additional MSc in Cognitive Sciences (1999) from the *Université Libre de Bruxelles*. He is making a PhD under the supervision of **Van Overwalle** on the way summary information is represented and processed in social judgments, and how this can be modelled by a connectionist network. Other fields of interest are implicit learning, neural networks, consciousness, self-consciousness and personality, and artificial intelligence.

Margeret **Heath** is a psychologist with a BA (1989) from the *University of Witwatersrand* in South Africa. She has been doing research as a visiting scholar at different institutes around the world, including the *University of Ottawa*, *International Institute for Management Development* (Switzerland), *St. Gallen University*, the *Santa Fe Institute*, and *George Mason University*. She moreover has many years of experience in business, mostly as a management consultant

specialized in facilitating collaboration and analysing and redesigning organizations. She is presently preparing a PhD on the possibility of radical novelty in distributed cognitive systems, under the supervision of **Van Overwalle**. Her interests include philosophy of mind and imagination, cybernetics, the extended mind, ethnographic methodologies, and collaborative inventiveness.

Marijke **Van Duynslaeger** studied Clinical Psychology at the *Vrije Universiteit Brussel*. She obtained her MSc in 2002 and an additional MSc in Cognitive Science from the *Université Libre de Bruxelles* in 2003. She is making a PhD under the supervision of **Van Overwalle**, on whether and in what contexts observers spontaneously infer the overt or hidden motives of a person when given information about that person's actions. This research project is funded by the FWO. Her other research interests include attitude formation and persuasive communication.

Klaas **Chielens** is a linguist with a MA (2003) in Germanic philology from the Vrije Universiteit Brussel. His Master's thesis [**Chielens**, 2002] made an empirical investigation of selection criteria for the spread of memes. He is working towards a PhD under the supervision of Heylighen on the same subject, funded by the Vrije Universiteit Brussel. He has practical experience with setting up websites, and managing student organizations. He is the new managing editor of the *Journal of Memetics*, assisting the editor, F. **Heylighen**, with the publishing and refereeing process.

Mixel **Kiemen** is a computer scientist with a MSc in Theoretical Informatics (2003) from the *Vrije Universiteit Brussel*. For his Master's thesis, he built a software agent simulation to investigate the creative process of tool-making. In 2004 he focused on "new media" and participated in the CONVIVIO summer course. Since the end of 2004, he is responsible for the Cartography of Research Actors project of *DISC*, the Brussels center for the knowledge society. His present research focuses on context-aware information technology to support virtual communities.

Marko **Rodriguez** is computer scientist with a BSc in Cognitive Science from the *University of California at San Diego* (2001), and a MSc in Computer Science from the *University of California at Santa Cruz* (2004). He was awarded a GAANN fellowship by the US Department of Education, which allows him to work as a researcher at ECCO. Together with D. Steinbock (Stanford University), he has developed the "particle-flow network" as a general methodology and software environment to model self-organization and distributed cognition. He has applied this to support collective intelligence in decision-making and scientific collaboration, and has written several papers on these topics. Marko is on track to receive his Ph.D in Computer Science from the *University of California at Santa Cruz*. In 2005, he will be working as a visiting researcher on distributed knowledge systems and digital libraries at the *Los Alamos National Laboratory* with J. **Bollen**.

Nick **Deschacht** has a MSc in applied economics (2001) from the Vrije Universiteit Brussel. His Master's thesis, on the long-wave theory of economic development applied to the emerging information society, got an award as the best one of its year within the social science faculty. He works presently as an assistant, teaching mathematics and statistics to social science students. He is interested in complex systems models of long-term socio-economic evolution, the information society, and the evolution of preferences.

Laetitia **De Jaegher** is a legal advisor who studied law at the *Université Catholique de Louvain-la-Neuve*, *Katholieke Universiteit Leuven*, *Rijksuniversiteit Leiden*, and

Moscow State University (1998). She is specialized in environmental and energy law and risk management. She has made several conference presentations and written a few papers on these issues, and has practical experience with project and knowledge management. Her research interests focus on developing a new framework for governance in a complex and changeful society, based on principles of self-organization and collective intelligence.

Erden **Göktepe** studied Political Science in *Ankara University* (1996) and the *Université Robert Schuman* (1999), and has an M.A. in International Relations from *Galatasaray University* (2004). He worked as research and teaching assistant at the *International Relations Department, Galatasaray University* in Istanbul, Turkey before joining ECCO in 2005. In his Master's thesis he approached international relations from the point of view of complexity theory and self-organising systems. He is preparing a PhD thesis on the emergence of cognitive actors as a part of complex social evolution in international politics, with F. **Heylighen** and G. Geeraerts as supervisors.

Dirk **Bollen** has a Master's degree in psychology (2003) from the *University of Maastricht*, with specialization in artificial intelligence and cognitive science. He worked as a teaching assistant at the faculty of psychology and guided some robotic workshops for students at the computer science department, University of Maastricht. He is interested in dynamical systems models of situated and embodied cognition, and their applications to the self-organization of multi-agent systems. His current research focus is on how high level cognition emerges from low level information integration and interaction between simple components.

2. Activities and achievements of the research team

2.1. Previous research

The Evolution, Complexity and Cognition group has been focusing on the self-organization [**Heylighen**, 1988; 2002; **Heylighen & Gershenson**, 2003] and evolution [**Heylighen, Bollen & Riegler**, 1999] of complex, cognitive systems, such as organisms, groups, societies and computer systems, from a transdisciplinary perspective inspired by systems theory and cybernetics [**Heylighen & Joslyn**, 1995, 2001]. Much of their research is theoretical, aimed at formulating fundamental principles [**Heylighen**, 1992] and integrating conceptual frameworks [**Heylighen**, 2000] to explain the emergence of intelligent organization in such systems. However, this work has also led to concrete technological applications in the design of a self-organizing, “learning” web, that assimilates the implicit knowledge of its users [**Bollen**, 2001; **Bollen & Heylighen**, 1998; **Heylighen & Bollen**, 2002], and the representation of knowledge through “bootstrapping” semantic and associative networks [**Heylighen**, 2001a, 2001b]. A related strand of work, on the selection criteria that determine which knowledge is transmitted in a large group [**Heylighen**, 1993; 1997; 1998] has received partial empirical confirmation from the statistical analysis of linguistic data [**Heylighen & Dewaele**, 2002; **Chielens & Heylighen**, 2005]. More recently, different models of cognition and learning were also investigated by means of multi-agent computer simulations [**Gershenson**, 2002, 2003, 2004] and “particle-flow” networks [**Rodriguez**, 2004; **Rodriguez & Steinbock**, 2004].

The Social Cognition Lab has worked mainly on causal attribution [**Van Overwalle & Heylighen**, 1995; **Van Overwalle, Heylighen, Casaer, & Daniëls**, 1992; **Van Overwalle & Timmermans**, under revision; submitted; **Van**

Overwalle, 1989; 1997a, b; 1998], implicit and spontaneous learning and inferences [**Timmermans & Cleeremans**, 2000; **Van Overwalle**, 2004; **Van Overwalle & Timmermans**, 2001; **Van Overwalle**, Drenth & Marsman, 1999], connectionist modeling of attribution phenomena [**Van Overwalle**, 1998, 2003, under revision; **Van Overwalle & Van Rooy**, 1998; 2001a, b; **Van Overwalle & Timmermans**, 2001] as well as connectionist modeling of social psychology at large. The latter have led to a series of publications on connectionist models, including one publication on group impression formation and biases in *Psychological Review* [**Van Rooy, Van Overwalle, Vanhoomissen, Labiouse & French**, 2003], two publications on person impression formation and cognitive dissonance in *Personality and Social Psychology Review* [**Van Overwalle & Jordens**, 2002; **Van Overwalle & Labiouse**, 2004] and forthcoming publications on attitude formation [**Jordens & Van Overwalle**, 2004; **Van Overwalle & Siebler**, submitted]. There is recent empirical work supporting some unique predictions of the connectionist approach on group processes and biases [**Vanhoomissen, De Haan & Van Overwalle**, submitted] and on attitude formation [**Jordens & Van Overwalle**, 2001; submitted].

2.2. *Teaching*

Frank **Van Overwalle** teaches three introductory and advanced courses on Social Psychology (with emphasis on social cognition), and one on Group Dynamics. These courses are followed by hundreds of students from different social sciences and humanities. He also teaches a course on Social Connectionism as a guest lecturer at the ULB, as part of the Master's program in Cognitive Sciences. Francis **Heylighen**, as a research professor, only teaches a single course on Complexity and Evolution for some 20 students in philosophy and ethics. He will teach a second one on Cognitive Systems in the planned new Master's programs in philosophy and cognitive psychology.

Both have been active in the formation of PhD students, from their own and other departments, by organizing and chairing series of seminars and discussions: the "Foundations Lectures" (1996-2001, **Heylighen** with other CLEA members), "CLEA/ECCO seminars" (2002-present, **Heylighen**) and "Boterhammen in de faculteit" (2002-present, **Van Overwalle**). These (mostly interdisciplinary) seminars have always been open to the whole academic community, and have attracted researchers from all the main departments of the university.

2.3. *PhD's delivered*

Several researchers have prepared and defended their doctorate within the research team, under the (individual or joint) supervision of **Van Overwalle** and **Heylighen**:

- Dirk **Van Rooy** [2000]
- Johan **Bollen** [2001]
- Bertin **Martens** [2004]
- Tim **Vanhoomissen** (defense scheduled June 2005)

The other members of the team are expected to defend their PhD within the next few years.

2.4. *Organization of conferences*

Both **Heylighen** and **Van Overwalle**, with their collaborators, have organized and chaired several international conferences and workshops on topics related to distributed cognition:

- International Symposium and Workshop on “Self-steering and Cognition in Complex Systems” (VUB, May 20-23, 1987). Proceedings: [**Heylighen**, Rosseel & Demeyere, 1990]
- Summer School on “Self-organization of Cognitive Systems” (Rijksuniversiteit Groningen, Netherlands, August 1988)
- 1st Workshop of the Principia Cybernetica Project: computer-supported cooperative development of an evolutionary-systemic philosophy (VUB, Belgium, July 2-5, 1991)
- Symposium “the Principia Cybernetica Project”, as part of the 13th Intern. Congress on Cybernetics (Namur, Belgium, August 1992)
- Symposium “Cybernetic Principles of Knowledge Development”, as part of the 12th European Meeting on Cybernetics and Systems Research, (Vienna, Austria, April 1994)
- Symposium “The Evolution of Complexity,” as part of the international congress “Einstein meets Magritte” (VUB, Belgium, June 1995). Proceedings: [**Heylighen**, **Bollen** & Riegler, 1999]
- 1st Symposium on “Memetics”, as part of the 15th Intern. Congress on Cybernetics (Namur, Belgium, August 1998)
- International Workshop “Classic and Connectionist Approaches to Causal Inference and Social Judgment” (Aix-en-Provence, France, 1999)
- International Workshop “From Intelligent Networks to the Global Brain” (VUB, Belgium, July 3-5, 2001) Proceedings: [**Heylighen** & **Heath**, 2005]
- One-day International Workshop on “Trends in Distributed Cognition: towards a formulation of a research agenda” (VUB, July 6, 2002)
- Workshops on “Social psychology in Belgium” (2002 and 2003).
- International Meeting on “Social Connectionism”, (16-19 June 2004, Genval, Belgium)
- Session on "Philosophy and Complexity" at the Complexity, Science & Society Conference (Liverpool, UK, 11-14 Sep., 2005)
- Symposium on "Social Connectionism" at the EAESP conference (Wurzburg, Germany, 26-25 July 2005)

2.5. *Contacts and collaborations*

Francis **Heylighen** and his students actively take part in several international networks related to collective knowledge development and information transmission: The *Principia Cybernetica Project* develops and manages a knowledge web (administered by **Heylighen**) that contains over 2000 documents, including many papers and complete electronic books, which are consulted some 60 000 times a day by people around the world. The *Global Brain Group*, co-founded and chaired by **Heylighen**, groups most of the important researchers in its domain (the emergence of computer-supported, collective intelligence at a world scale), including V. Turchin, B. Goertzel, J. de Rosnay, G. Stock and C. Joslyn. The group organized the first conference on the domain. **Heylighen** administers its electronic mailing list which is used by over 100 selected contributors to discuss advanced issues. **Heylighen** is also involved as editor-in-chief and founding editorial board member in the *Journal of Memetics: Evolutionary Models of Information Transmission*, where most researchers in the domain publish.

His group has been closely collaborating for many years with the *Distributed Knowledge Systems and Modelling* team, led by C. Joslyn at *Los Alamos National Laboratory*, producing several joint publications [e.g. **Heylighen** & Joslyn, 1993,

1995, 2001; Rocha & Bollen, 2000]. They also have kept in contact for many years with B. Edmonds in the *Center for Policy Modelling* (Manchester Metropolitan University) and S. Umpleby, director of the *Center for Social and Organizational Learning*, *George Washington University*, and many other researchers in the domain of systems theory and cybernetics.

At the international level, Frank **Van Overwalle** collaborates with renowned researchers in the area of connectionist modeling of social phenomena, including Eliot Smith (*Purdue University*, USA), Stephen Read (*USC, Los Angeles*), Yoshi Kashima (*University of Melbourne*, Australia), and Fred Vallée-Tourangeau (*University of Hatfield*, U.K.). He is also a member of a research community of the FWO on “Acquisition and representation of evaluative judgments and emotion”. There is also intense collaboration and joint publications with well-known connectionist researchers in other domains of psychology in Belgium, such as at the *Université Libre de Bruxelles* (Axel Cleeremans) and *Université de Liège* (Robert French; Christophe Labiouse).

Locally, within the *Vrije Universiteit Brussel*, our research team maintains and plans to further develop a variety of interdisciplinary contacts, including N. Gontier and J-P. Van Bendegem at the Center for Logic and Philosophy of Science (CLWF) on the evolution of language and the extended mind, E. Verstraeten and E. Soetens of the Cognitive and Physiological Psychology group (COPS) on brain physiology and implicit learning, G. Geeraerts and K. Laforce of the Political Science Department (POLI) on complex systems models of social interaction, L. Steels of the AI-lab on computer simulations of cognitive and language evolution, B. Manderick and A. Nowé of the Computational Modelling Lab (COMO) on multi-agent systems, and G. Vancronenburgh, and T. Coenen of the Economics Department (MOSI) on evolutionary and systems dynamics models of social and economic interaction.

At our sister university, the *Université Libre de Bruxelles*, we plan to stay in touch with T. Lenaerts of the AI-lab (IRIDIA) on the evolution of cooperation, A. Cleeremans of the Cognitive Science Research Unit on connectionist models of cognition, the group around J-L. Deneubourg at the Unit of Social Ecology on animal models of collective intelligence, and O. Klein at the Social Psychology Department on communication and maintenance of stereotypes in groups.

3. Introduction to the research theme

3.1. A connectionist perspective on cognition

Cognition can be defined as the processing of information by an agent in order to support understanding, decision-making and problem-solving. The cognitive agent uses its *knowledge* to interpret incoming data or stimuli, derive inferences from it, and select actions appropriate to the thus perceived situation and to its internal preferences. This knowledge is in general the result of previous *learning*, i.e. adapting the internal structure responsible for processing the information so as to maximize the quality of the inferred predictions and selected actions, while taking into account the feedback from the environment.

From this “cybernetic” perspective [Heylighen & Joslyn, 2001; Van Overwalle & Van Rooy, 1998; Van Overwalle 1998; Van Overwalle & Labiouse, 2003], knowledge is not a discrete collection of beliefs, propositions or procedures, but a continuously evolving network of connections between perceptions, interpretations and actions, which allows the agent to anticipate and adapt to changes in its environment [Heylighen, 1990]. Thus, the understanding of a situation that knowledge enables can be seen as a form of preparedness, expectation, or anticipation for what may come [Neisser, 1976]. The anticipatory

connections between perceptual, abstract, and motor categories have the general form $A \rightarrow B$ [Heylighen, 2001a], which can be interpreted as:

IF occurrence of category A (e.g. *banana* or *lack of preparation*),
THEN expect occurrence of category B (e.g. *yellow* or *failure for exam*)
with a certain probability

Such basic connections underlie not only prediction, but causal attribution or explanation of B , given A [Van Overwalle & Heylighen, 1991, 1995; Van Overwalle, 2003].

The collection of weighted connections $\{A \rightarrow B, A \rightarrow C, C \rightarrow B, B \rightarrow D, B \rightarrow E, E \rightarrow A, \dots\}$ defines an associative or connectionist network [Heylighen, 2001a]. Such a network can perform complex inferences by activating the initial or perceived categories, letting the activation propagate recurrently through connected categories, and noting which "inferred" or output categories gather most activation. The connections and their continuously varying weights can be learned through the closely related *Hebbian* [e.g. Heylighen & Bollen, 2002] algorithm, which reinforces the connection between concepts each time they are co-activated, and *Delta* algorithm [Van Overwalle, 1998, 2003; Van Overwalle & Van Rooy, 1998, 2001a,b], which reinforces connections that match outside activation sequences.

3.2. Cognition at the social level

The study of cognition—*cognitive science*—is in essence multidisciplinary, integrating insights from approaches such as psychology, philosophy, artificial intelligence (AI), linguistics, anthropology, and neurophysiology. To this list of sciences of the *mind*, we now also must add the disciplines that study *society*. Indeed, an increasing number of approaches are proposing that cognition is not limited to the mind of an individual agent, but involves interactions with other minds.

Sociologists [e.g. Berger & Luckman, 1967] have long noted that most of our knowledge of reality is the result of a social construction rather than of individual observation. Philosophers [e.g. Searle, 1995] and cyberneticians [e.g. Heylighen & Joslyn, 2001] have pointed out the profound implications of this observation for epistemology and theory of mind.

The nascent science of memetics [Aunger, 2001; Heylighen, 1998], inspired by evolutionary theory and culture studies, investigates the spread of knowledge from the point of view of the idea or *meme* being communicated between individuals rather than the individual that is doing the communication.

Economists too have studied the role of knowledge in innovation, diffusion of new products and technologies, and the organization of the market. More recently, they have begun to understand its essential role in social and economic development [Martens, 1998, 2005]. Management theorists emphasise knowledge management and learning as an organisational phenomenon rather than as an individual process. Effective organisational learning is deemed to be the difference between an enterprise that flourishes and one that fails [Senge, 1990].

Biologists and computer scientists have built models that demonstrate how collectives of simple agents, such as ant colonies, bee hives, or flocks of birds, can process complex information more effectively than single agents facing the same tasks [Bonabeau et al., 1999]. Building on the tradition of distributed artificial intelligence which studies the interactions and collaborations within a system of intelligent software agents [Weiss, 1999; Gershenson, 2001], the subject of

collective cognition is now even being investigated mathematically [Crutchfield et al. 2002].

These different approaches provide a new focus for the understanding of cognition that might be summarized as *collective intelligence* [Levy, 1997; **Heylighen**, 1999; **Rodriguez**, 2004], i.e. the cognitive processes and structures that emerge at the social level.

3.3. Empirical studies of social cognition

Psychologists too have studied cognition at the group level, using laboratory experiments to document various biases and shortcomings of collective intelligence [e.g. Brauer et al., 2001; Klein et al., 2003; **Van Rooy, Van Overwalle** et al., 2004]. Social psychology has a long record of research on the cognitive processes responsible for the formation of stereotypic impressions about other groups and for the lack of efficiency in group problem-solving.

Research has revealed that we often fall prey to biases and simplistic impressions about other groups, and that many of these distorted representations are emergent properties of our cognitive dynamics. Some of these biased processes are *illusory correlation* or the creation of an unwarranted association between a group and undesirable characteristics, *accentuation* of differences between groups, *subtyping* of deviant members [for a review see **Van Rooy, Van Overwalle, Vanhoomissen** et al., 2003] and the *communication* of stereotypes [e.g., Lyons & Kashima, 1993]. Many of these processes have been modeled by connectionist networks [**Van Rooy** et al., 2003].

With respect to processes within a group, different types of social dynamics lead to a less than optimal performance. These include *conformity* and *polarization* which move a group as a whole towards more extreme opinions [Ebbesen & Bowers, 1974; Mackie & Cooper, 1984; Isenberg, 1986], *groupthink* that leads to unrealistic group decisions [Janis, 1972], the lack of *sharing of unique information* so that intellectual resources of a group are underused [Larson et al., 1996, 1998; Stasser, 1999; Wittenbaum & Bowman, 2003] and the suboptimal use of relevant *information channels* in social networks [Leavitt, 1951; Mackenzie, 1976; Shaw, 1964].

3.4. The extended mind

The investigation of cognition has expanded not only in the direction of social systems but in that of the physical environment. The failure of traditional, “symbol-processing” AI to come up with workable models of intelligence has pointed to the necessity for *situatedness*, *embodiment* or *enaction* [Steels & Brooks, 1995; Clark, 1997; Susi & Ziemke, 2001]. This refers to the observation that cognition or mind cannot function in a mere abstract realm of symbols, logical propositions or Platonic ideas (the “brain-in-a-vat”), but must be part of an interaction loop with a concrete environment, via the bodily functions of perception and action [cf. **Heylighen** & Joslyn, 2001].

One of the implications is that there is no need for complex internal representations and symbol manipulations to precisely predict the state of the environment when sensory-motor feedback allows the system to continuously adjust its expectations to the actual situation [**Bollen**, 2004]. This has led to a flurry of interest in autonomous robots which forego complex processing by using the environment as its own best model [Steels & Brooks, 1995].

The environment supports cognition not just *passively*—by merely representing itself, but *actively*—by registering and storing agent activities for future use, and thus functioning like an external memory [Kirsh, 1996; Kirsh & Maglio, 1994; Clark, 1997]. Examples abound, from the laying of pheromone trails by ants and the use of branches to mark foraging places by wood mice to the

notebooks we use to record our thoughts. Physical objects can further be used to collect and process information, as illustrated by telescopes and computers. This use of external phenomena as “epistemic structures” [Kirsh & Maglio, 1994] that support internal information processing leads to a view of cognition expanding outside the brain: the *extended mind* [Clark & Chalmers, 1998]. This is an active form of the philosophy of *externalism*, according to which external phenomena take part in mental content.

The “offloading” of information onto the environment makes this information potentially available for other agents, thus providing a medium by which information sharing, communication, and coordination can occur. This basic mechanism, known as *stigmergy*, underlies many examples of collective intelligence [Bonabeau et al., 1999; Heylighen, 1999; Susi & Ziemke, 2001], such as the trail laying of ants and the mound building of termites. More generally, any form of information exchange between agents requires the use of external media, such as sound waves, light, or electrical signals. Thus, the two perspectives of collective intelligence and situatedness necessarily tie in with each other.

They can be integrated under the heading of *distributed cognition* [Hutchins, 1995; Hollan, Hutchins & Kirsh, 2001]: to understand complex information processing, we must consider the distributed organization constituted by different individuals with different forms of knowledge and experience, the social network that links them together, and the artefacts, media or information technologies that support their individual thought and interindividual communication. The central idea is that the processing occurs through what Hutchins [1995] calls *the propagation of representational states across representational media*.

Hutchins, and his collaborators at UCSD and Indiana (Kirsh, Hollan, Maglio et al.) have begun to develop highly refined ethnographic research methodologies in order to map what they call Wild or Raw cognition, i.e. information processing as it happens in the real world rather than in a laboratory set-up or computer simulation. The paradigmatic example investigated in detail through this methodology is the navigation of a large ship, which requires the activity of several people coordinated by means of instruments, ship navigation manuals, communication channels, and the necessary enacted/situated deviation from guidelines and formal process [Hutchins, 1995].

4. Aim: towards an integrated theory of distributed cognition

In spite of its promises, the distributed cognition approach as yet offers little more than a heterogeneous collection of ideas, observation techniques, preliminary simulations and case studies. It lacks a coherent theoretical framework that would integrate the various concepts and observations, and provide a solid foundation for building detailed models of concrete systems and processes [Heylighen, Heath & Van Overwalle, 2004; Susi & Ziemke, 2001]. The present proposal aims to develop such an integrated theory, supported by observations, experiments and detailed computer simulations.

For us, understanding distributed cognition at the deepest level requires understanding how it *originates*. The analysis of existing distributed processes, such as ship navigation, is not sufficient, because the underlying systems tend to be constrained and specialized, while their often convoluted way of functioning is typically rigidly set as the result of a series of historical accidents. A more general understanding, not only of the “how?” but also the “what?” and the “why?”, may be found by analysing how distributed cognition emerges and evolves in a system that initially does not have any cognitive powers, in other words how it *self-organizes*. We wish to focus on the *creation*—and not merely the propagation—of knowledge and information in these systems.

Our basic research questions can be formulated as follows:

- How do initially independent agents organize themselves into a distributed cognitive system?
- What kind of coordination between their different information processing activities can they achieve?
- What knowledge is novel or emergent in this system, i.e. knowledge that did not already exist in the mind of an individual agent?
- In what way is this emergent cognition better or worse than the initial, individual cognition?
- More specifically, which information is lost or filtered out during the process?
- Which factors determine the efficiency of the process? For example, in how far do the resulting cognitive capabilities depend on the number of agents, the diversity between agents, or the presence of different types of tools or media?

An answer, even quite incomplete, to these questions would provide us with the basis for building an integrated theory of how distributed cognition self-organizes and what this implies for the resulting organization.

5. Social relevance and potential applications

A theory of distributed cognition as we envisage it here would offer a wealth of potential applications, with particular relevance to society at large. While our aim is in the first place to do basic research and reach a general understanding of the problem domain, we are likely to take a closer look at several of these application domains so as to confront our models with the practical issues that surround distributed cognition in reality, as contrasted with laboratory or theory.

To start with, understanding how knowledge and information are distributed throughout social systems would help to foster the economic and social development that new knowledge and better coordination engenders [Martens, 1998; 2005]. In particular, such a theory should tell us how important new ideas can diffuse most efficiently, and conversely how the spread of false rumours, superstitions and “information parasites” can be held in check [Heylighen, 1999; Chielen & Heylighen, 2005]. More generally, it may help us to control for the cognitive biases and social prejudices whose ubiquity psychologists have amply demonstrated [Brauer et al., 2001; Klein et al., 2003; Van Rooy, Van Overwalle et al., 2004].

On a smaller scale, a theory of distributed cognition has immediate applications in business, government, and other organizations. It would help them to promote innovation and avoid the pitfalls of collective decision-making, such as *conformity* or *groupthink* [Janis, 1972], which stifle creativity. It would support organizations not only in generating new knowledge but in efficiently conserving, applying and managing the knowledge that is already there. More fundamentally, it would provide us with concrete guidelines to design more flexible, “self-organizing” organizations, where roles and functions adapt to the present context, and where information is processed in a coordinated way, with a minimum of loss, distortion, misunderstanding or confusion. In sum, it would foster the collective intelligence of the organization, while minimizing the inherent tendency of groups towards “collective stupidity”.

This is particularly important for supranational organizations, such as the European Union, United Nations or World Trade Organization, which have coalesced out of the collaborations between very diverse and largely autonomous actors. The complexity of the problems at the international level, such as the need for sustainable development, risk management, security threats, and management of the global ecosystem, calls for new methods of information integration and *governance* [De Jaegher, 2003]. Ideally, these would be based on bottom-up self-

organization and collective intelligence rather than on the top-down imposition of rules that characterizes traditional bureaucracies. A promising approach is the use of distributed information systems to support various forms of collective decision-making or e-democracy [Rodriguez, 2004; Rodriguez & Steinbock, 2004].

Another promising application domain is the support of scientific research and collaboration between researchers from different disciplines and institutions. With the present information explosion, it is difficult for a scientist to remain informed about the most relevant work in his or her domain. However, we can use models of distributed cognitive self-organization to analyse and optimize the implicit social and knowledge networks formed by the connections between researchers (e.g. co-authorship) and their publications (e.g. citation) [Heylighen, 1999; Heylighen & Bollen, 2002]. This makes it possible to find the most pertinent papers, journals, potential collaborators or referees for a given research project, and thus promote a more efficient propagation of information across the scientific community [Rodriguez, 2005]

More specifically technological applications abound as well. Another important application of the proposed model of distributed cognition would be the compilation by committees of experts of formal “ontologies” [Staab & Studer, 2003], i.e. the systems of categories and links necessary for the *semantic web* [Berners-Lee et al., 2001]. This knowledge architecture for the future Internet will allow users to get concrete answers to specific questions, while enabling various services to automatically coordinate. But this requires efficient and consensual schemes to represent knowledge that is generated and managed in a distributed manner.

More generally, a lot of research is going on in distributed AI [Weiss, 1999] to develop efficient coordination schemes to let software or hardware agents collaborate [e.g. Dastani et al., 2001]. One of the more immediate application domains is *ambient intelligence* [ISTAG, 2003]. This refers to the vision of everyday artefacts and devices such as mobile phones, coffee machines and fridges exchanging information and coordinating with each other so as to provide the best possible service to the user, without needing any programming or prompting—thus effectively extending the user’s mind into his or her physical environment [Gershenson & Heylighen, 2004].

Integrating the ambient intelligence of devices, the collective intelligence of organizations and society, and the global communication and coordination medium that is the future Internet leads us to a vision of a *global brain* [Heylighen & Bollen, 1996; Heylighen, 1999; Heylighen & Heath, 2005], i.e. the emerging intelligent network formed by the people of this planet together with the knowledge and communication technologies that connect them together.

6. Basic assumptions

Building on the results of our previous research, we propose five general assumptions, to function as building blocks or starting points out of which we will try to develop a detailed model of distributed cognition. These should not in themselves be seen as hypotheses to be verified or falsified through experimental tests, but as heuristic postulates that will allow us to produce more concrete, hypotheses that can be tested through simulations and experiments.

6.1. Groups of agents self-organize

Consider a group of initially autonomous actors, actants or *agents*, where an agent can be human, animal, social or artificial. Agents by definition perform *actions*. Through their shared environment the action of the one will in general affect the

other. Therefore, agents in proximity are likely to *interact*, meaning that the changes of state of the one causally affect the changes of state of the other. These causal dependencies imply that the agents collectively form a *dynamical system*, evolving under the impulse of individual actions, their indirect effects as they are propagated to other agents, and changes in the environment. This system will typically be non-linear, since causal influences normally propagate in cycles, forming a complex of feedback loops. Moreover, a dynamical system has computational structure and is therefore in principle able to process information and generate patterns [Crutchfield, 1998].

While such a complex system is inherently very difficult to model, control or predict, all dynamical systems tend to *self-organize* [Ashby, 1962; **Heylighen & Joslyn**, 2001; **Heylighen**, 2003; **Heylighen & Gershenson**, 2003], i.e. evolve to a relatively stable configuration of states (an *attractor* of the dynamics). We can say that the agents in this configuration have mutually *adapted* [Ashby, 1962], limiting their interactions to those that allow this collective configuration to endure. Indeed, the system as a whole can be seen as an ecosystem of co-evolving or mutually adapting subsystems (agents and their rules for action).

This ecosystem can always be decomposed into a single agent and its environment, i.e. the whole of the other agents and non-agentive elements (objects) that affect the agent. Since we assume that a single agent can vary its repertoire of action rules while preferring situations that bring individual benefit, action strategies will undergo a trial-and-error or variation-and-selective-retention dynamics [Heylighen & Campbell, 1995], leading agents to learn better action rules and thus become better adapted to the overall ecosystem.

In addition to this individual adaptation, co-evolution is driven by a selective pressure on the agents and their action strategies to make their interactions more cooperative or *synergetic* [Corning, 1995; Wright, 2000; **Heylighen**, 2004], because in the long term a mutually beneficial interaction is preferable to one that is less so. As illustrated by the many multi-agent simulations of the evolution of cooperation [e.g. Axelrod, 1984; Riolo, Cohen & Axelrod, 2001; Hales & Edmonds, 2003], this fosters the evolution of strategies that overcome the fundamental obstacle of individual selfishness or “free riding”, as exemplified by the classic Prisoners’ Dilemma game [Axelrod, 1984; **Heylighen**, 1992; **Heylighen & Campbell**, 1995].

From this perspective, the self-organization and further evolution of the collective configuration appears to create a form of *social organization*, in which agents support each other’s activities. This configuration can be viewed as a *mediator*, coordinating the agents’ actions so as to minimize conflict or friction and maximize collective benefit [Heylighen, 2004]. A simple example of a mediator is the system of traffic rules, traffic signs, road markings and traffic lights that together regulate the movement of cars, minimizing mutual obstruction and maximizing overall throughput [Gershenson, 2005].

According to *coordination theory* [Crowston, 2003], we can distinguish the following fundamental dependencies between activities or processes in an organization: 1) two processes can use the same resource (input) and/or contribute to achieve the same task or goal (output); 2) one process can be prerequisite for the next process (output of the first is input of the second). The first case calls for tasks to be performed in *parallel* and the second case in *sequence*. Efficient organization means that the right activities are performed by to the right agents at the right time. The parallel distribution of activities determines the *allocation of resources* and *division of labor* between agents. The sequential distribution determines their *workflow*.

Division of labor reinforces the specialization of agents, allowing each of them to develop an expertise that the others do not have [Gaines, 1994; **Martens**, 2005]. This enables the collective to overcome individual cognitive limitations, accumulating a much larger amount of knowledge than any single agent might. Workflow allows information to be propagated and processed sequentially, so that

it can be refined at each stage of the process. Self-organization thus potentially produces emergent cognitive capabilities that do not exist at the individual level.

6.2. *The organization co-opts external media for information exchange*

Self-organization in this sense can be seen as the more efficient, synergetic use of interactions. Interactions between agents necessarily pass through their shared physical environment. We will call the external phenomena that support these interactions *media*.

Certain parts or aspects of the environment lend themselves better to synergetic interaction than others do. For example, a low-bandwidth communication channel that is difficult to control, such as smoke signals, will support less synergetic interactions than a reliable, high-bandwidth one, such as optical cable. Thus, there is a selective pressure for agents to preferentially use the more efficient media, i.e. the ones through which causal influences—and therefore information—are transmitted most accurately and reliably.

Moreover, simply by using them, the agents will change the media, generally adapting them to better suit their purposes. For example, animals or people that regularly travel over an irregular terrain between different target locations (such as food reserves, water holes or dwellings) will by that activity erode paths or trails in the terrain that facilitate further movement. The paths created by certain agents will attract and guide the movements of other agents, thus providing a shared coordination mechanism or mediator that lets the agents communicate indirectly. Thus, actions (trajectories of movement) and media (tracks eroded in the terrain) co-evolve, the one adapting to better fit the other. A more advanced version of this mechanism are the trails of pheromones laid by ants to steer other members of their colony to available food sources, thus providing the colony with a *collective mental map* of its surroundings [Heylighen, 1999]. Humans, as specialized tool builders, excel in this adaptation of the environment to their needs, and especially in the use of physical signs and symbols, electromagnetic waves, or hardware to store, transmit and process information.

In this way, external media are increasingly assimilated or co-opted into the social organization, shaping it while being shaped by it, and making the organization's functioning ever more dependent on them. As a result, the collective cognitive system is extended into the physical environment and can no longer be separated from it.

6.3. *Distributed cognitive systems function like connectionist networks*

A core assumption of our approach is that the connectionist organization that characterizes cognition within the human brain also characterizes cognition distributed across brains. When we consider an extended social organization at the most abstract level, we can distinguish *nodes*, i.e. the agents or physical objects that store or process information, and *connections*, i.e. the media, communication channels or relationships along which information is transmitted. They represent stabilized causal relations between agents and/or objects, possibly supported by co-opted media. A connection $A \rightarrow B$ has a variable *strength*, which depends on the ease, frequency or intensity with which information is transmitted. This strength can be seen as the conditional probability or degree of expectation that a piece of information arriving in A will be directly transmitted to B.

Every node is characterized by its space of possible states. The actual state at the beginning of a process is propagated in parallel along the different connections, and recombined in the receiving nodes. State spaces can in general be factorized into independent variables or degrees of freedom, each of which can take on a continuum of values [Heylighen, 2002]. A complex node can thus be functionally decomposed as an array of simple, one-dimensional nodes that only take on a

single “intensity” or “activation” value. The resulting network of simple nodes and connections appears functionally equivalent to an “artificial neural network”, or what we prefer to call a *connectionist network*, where activation spreads from node to node via variable strength connections [Van Overwalle & Labiouse, 2004; McLeod et al., 1998]. This network is in general *recurrent*, because of the existence of cycles or loops as mentioned earlier.

Connectionist networks have proven to provide very flexible and powerful models of cognitive systems [e.g. McLeod et al., 1998; Van Overwalle & Labiouse, 2004; Timmermans & Cleeremans, 2000]. Their processing is intrinsically parallel and distributed [Rumelhart & McClelland, 1986]. Because of the inherent redundancy, they are much more robust than sequential architectures, surviving destruction of part of their nodes and connections with merely a “graceful” degradation of their performance. These systems are wholly decentralized and self-organizing, eliminating the need for a central executive that deliberately processes information. Moreover, since activation spreads automatically from the nodes that received the initial stimuli to associated nodes, connectionist networks can complete and generalize patterns. Thus, they can fill in lacking data and infer plausible conclusions on the basis of very limited information.

Most importantly, connectionist networks inherently support learning, by means of the continuous adaptation of the connection strengths to the ways in which they are used. Thus, successfully used connections become stronger, making it easier for information to be propagated along them, while connections that are rarely used or whose use led to erroneous results weaken, and eventually disappear.

In an extended cognitive system we can conceive of at least two mechanisms for such selective reinforcement. On the physical level, commonly used media become more effective, as proposed in the previous hypothesis.

But a more flexible mechanism is social acquaintance, in which an agent learns from the experience of communicating with another agent. If the other agent reacts appropriately, the first agent will increase its *trust* in the other’s competence and goodwill, and thus becomes more likely to transmit information to that agent in the future. Similarly, the receiving agent learns to trust the sender more, and thus will pay more attention to the sender’s messages and requests. Such trust-based or acquaintance-based connections form the basis of what is known as a *social network* [e.g. Rodriguez & Steinbock, 2004] which can be seen as an aspect of our more encompassing concept of a distributed connectionist network. From a cognitive point of view, trust is the basic relation of confidence or *expectation* that a certain agent will react in a certain way with a certain probability [cf. Castelfranchi & Falcone, 2000]. Thus, trust can be seen as a direct extension from the internal, cognitive connections between the concepts within an agent’s memory to the external, social connections between agents that allow them to form a distributed cognitive system.

The network’s “experience” of use is stored in long-term weight changes of its connections. Thus, the network acquires new knowledge in a distributed manner, i.e. storing it in the pattern of connections and not just in the states or memories of individual nodes. An example of such a distributed learning system is the *invisible hand* of the market, which “knows” how to make supply match demand by allocating resources to the agents that appear most competent to satisfy the demand [Heylighen, 1997, 2004].

6.4. Information in the network is propagated selectively

Whether information is transmitted will not only depend on the architecture of the network, but on the content of the information. Memetic analysis and social-psychological observation have suggested different selection criteria that specify

which information is preferentially passed on [Heylighen, 1993, 1997, 1998; Chielens & Heylighen, 2005]. These include the criteria of:

- *utility* (the information is useful or valuable to the agents)
- *novelty* (the information is not already known)
- *coherence* or *consistency* (the information is consistent with the knowledge that the agents already have)
- *simplicity* (since complex information is difficult to process and transmit, less important details tend to be left out)
- *authority* or *trust* (the source of the information is recognized as being trustworthy)
- *conformity* or *consensus* (the majority of agents agree on the information)
- *expressivity* (the information can be easily expressed in the available media)
- *formality* or *explicitness* (the less context or background communicating agents share, the more important it is to express the information explicitly)

Several of these criteria have been empirically confirmed through psychological experiments [Lyons & Kashima, 2003] and analysis of linguistic data [Heath, Bell & Sternberg, 2001; Heylighen & Dewaele, 2002; Chielens & Heylighen, 2005]. They provide a simple set of guidelines to understand the evolution of distributed knowledge through the variation and selective transmission of propagating fragments of information [Heylighen, 1993, 1998].

A theory of distributed cognition would ideally allow these criteria to be derived from the dynamics of a distributed connectionist network, rather than have them posited to some degree *ad hoc*. A first simulation [Van Overwalle, Heylighen & Heath, 2005] indeed suggests that this can be achieved. For example, the reinforcement of connections through the increase of trust builds authority for the sending agents, while telling them which information the receiving agents are likely to already know and agree with, making it less important for them to transmit detailed, explicit reports. Moreover, spread of activation along existing connections will automatically attenuate inconsistent [Van Overwalle & Jordens, 2002] or complex signals, while amplifying signals that are confirmed by many different sources (conformity) or that activate in-built rewards or punishments (utility).

Selective propagation and thus filtering out of less relevant or less reliable data already constitutes information processing, as it compresses the data and thus potentially distils the underlying pattern or essence. However, if selectivity is inadequate, this can lead to the loss of important ideas, and the propagation of incorrect information, as exemplified by the flurry of social and cognitive biases that characterizes “groupthink” [Van Rooy, Van Overwalle, Vanhoomissen et al., 2003]. More extensive modelling and simulation should allow us to identify the central factors through which we can control these dangerous tendencies.

6.5. Novel knowledge emerges

On the positive side, groups often are more intelligent than individuals, integrating information from a variety of sources, and thus overcoming individual biases, errors and limitations. In the simplest case, this occurs through a mere aggregation or superposition of individual contributions [Surowiecky, 2004]. Because of the law of large numbers, the larger the variety of inputs, the smaller the overall effect of random errors, noise, or lacking data, and the clearer and more complete the resulting collective signal [Heylighen, 1999]. This “averaging” of contributions is represented very simply in a connectionist network, by the activation from different inputs being added together and renormalized in the target nodes.

But a recurrent connectionist network, being non-linear and self-organizing, can offer more radical forms of novelty creation, through the emergence of structures that are more than the sum of their parts. Rather than being attenuated by averaging, noise can here play a creative role, triggering switches to a wholly new attractor or configuration at the bifurcation points of the dynamics, thus exemplifying the “order from noise” principle [von Foerster, 1960; **Heylighen**, 2002; **Heylighen & Gershenson**, 2003].

The same mechanisms of self-organization that lead to coordination between agents are also likely to lead to coordination and integration of the ideas being communicated between those agents. An idea that is recurrently communicated will undergo a shift in meaning each time it is assimilated by a new agent, who adds its own, unique interpretation and experience to it. Moreover, the need to express it in a specific medium will also affect the shape and content of the message, which will be further constrained by the need to achieve an invariant external reference or “intentionality” for it [Cantwell Smith, 1996]. Like in a game of Chinese whispers [cf. Lyons & Kashima, 2003], by the time the idea comes back to the agent who initiated it, it may have changed beyond recognition. After several rounds of such passing back and forth between a diverse group of agents, the dynamical system formed by these propagations with a twist is likely to have reached an attractor, i.e. an invariant, emergent configuration.

In this way, novel shared concepts may self-organize through communication, providing a basic mechanism for the social construction of knowledge [Berger et al., 1967]. Concrete illustrations of this process can be found in multi-agent simulations of the origin of language where the symbol (external support) co-evolves with the category that it refers to (internal concept with external reference) [e.g. Hutchins & Hazelhurst, 1995; Steels, 1998; Belpaeme, 2001]. These models are based on recursive *language games*, where a move consists of one agents expressing a concept and the receiving agent indicating whether or not it has “understood” what the expression refers to (e.g. by pointing towards a presumed instance of the category), after which the first agent adjusts its category and/or expression. After a sufficient number of interaction rounds between all the agents in the collective, a “consensus” typically emerges about a shared concept and its expression.

Knowledge consists not only of concepts or categories, but of logical and causal connections between these categories. As noted in 3.2, connections can be learned through the *Hebbian* [e.g. **Heylighen & Bollen**, 2002] or *Delta algorithms* [Van Overwalle, 1998, 2003; Van Overwalle & Van Rooy, 1998, 2001a,b]. These connectionist learning rules are simple and general enough to be applicable even when cognition is distributed over different agents and media [e.g. **Heylighen & Bollen**, 2002; **Bollen**, 2001; **Van Overwalle, Heylighen & Heath**, 2005; Heylighen, **Heylighen, Bollen & Casaer**, 2005], as argued in 6.3.

However, if we moreover take into account the social construction of concepts, we get a view of concepts, symbols, media and the connections between them co-evolving, in a complex, non-linear dynamics. This points us towards a potential “bootstrapping” [**Heylighen**, 2001a] model of how complex and novel distributed cognitive structures, such as languages, scientific theories, world views and institutions, can emerge and evolve.

7. Methodologies for distributed cognition research

The study of distributed cognition is in essence multidisciplinary, and our research therefore will need to integrate methods from very different traditions, including theoretical analysis and model-building, computer simulation and empirical observation.

7.1. Theoretical investigation

The very wide variety of existing models, concepts and observations makes it clear that in order to elaborate our working assumptions into a full theory we first of all need to focus on the collection and theoretical integration of existing models and observations. This will require an on-going review of the relevant literature in the many related disciplines, and the consultation of a variety of domain experts.

Happily, our team has the required multidisciplinary expertise, its members having degrees in cognitive science, psychology, computer science, political science, law, linguistics and economics; advanced research experience in philosophy, cybernetics, connectionism, management, self-organization and complex systems; and local and international contacts with a range of specialists in the relevant research topics. Moreover, we have extensive experience in interdisciplinary integration [e.g. **Heylighen**, 1992; 1990b], sometimes in the form of connectionist models [e.g., **Van Overwalle**, 1998; **Van Overwalle & Jordens**, 2002; **Van Overwalle & Labiouse**, 2003], and in both traditional (workshops, seminars, ...) and computer-supported forms (mailings lists, web-based discussion forums, ...) of intellectual discussion and collaboration [**Heylighen**, 2000].

A more specific methodology for theoretical research that is increasingly popular among philosophers is the *thought experiment*: imagine a system with such and such characteristics, put in such and such circumstances; what will happen? Different models and approaches will typically make different predictions. Theoretical analysis and inference will then allow us to find out in what respect the models agree or disagree, highlighting their similarities and differences and thus giving us a common basis to integrate them. A well-chosen thought experiment may moreover help us to find out that certain models are incoherent (self-contradictory), inconsistent with known facts, or simply incomplete and ambiguous. This will help us to focus on the issues that need to be investigated further, or complemented by other approaches.

7.2. Computer simulation

A more advanced version of a thought experiment is a computer simulation [**Gershenson**, 2002a]. Here we make the theoretical model sufficiently explicit so that its rules can be programmed. The advantage is that the computer can explore many more possible combinations of initial conditions, and infer many more of their consequences than a theoretician can. Thus, a well-designed simulation platform can provide us with a true *virtual laboratory* [**Gershenson, González & Negrete**, 2000], which we can use to quickly and easily test thousands of variations on a basic model simply by varying the parameter values. Such a virtual laboratory can even be used to compare the predictions of fundamentally different paradigms for modelling cognition, such as dynamical systems, connectionist networks and rule-based systems, by programming agents to behave according to each of the models and then registering in what way their concrete behaviors differ [**Gershenson**, 2003, 2004].

Work in the collective intelligence/distributed AI tradition has typically relied on *multi-agent simulations* (MAS), in which interacting software agents form a kind of “artificial society” [Bonabeau et al., 1998; Weiss, 1999]. An alternative simulation paradigm are the connectionist networks, which tend to give more precise, numerical predictions than MAS, but tend to be less effective in providing an intuitive, qualitative understanding of the system that is modelled. Our research team has extensive experience with both types of simulations [e.g. **Gershenson**, 2003; **Van Rooy, Van Overwalle, Vanhooymissen** et al. 2003; **Rodríguez**, 2004]. Most recently, we have started to develop an integrated framework where connectionist agents interact through “extended” communicative connections, as proposed in hypothesis 6.3 [**Van Overwalle, Heylighen & Heath**, 2005]. This

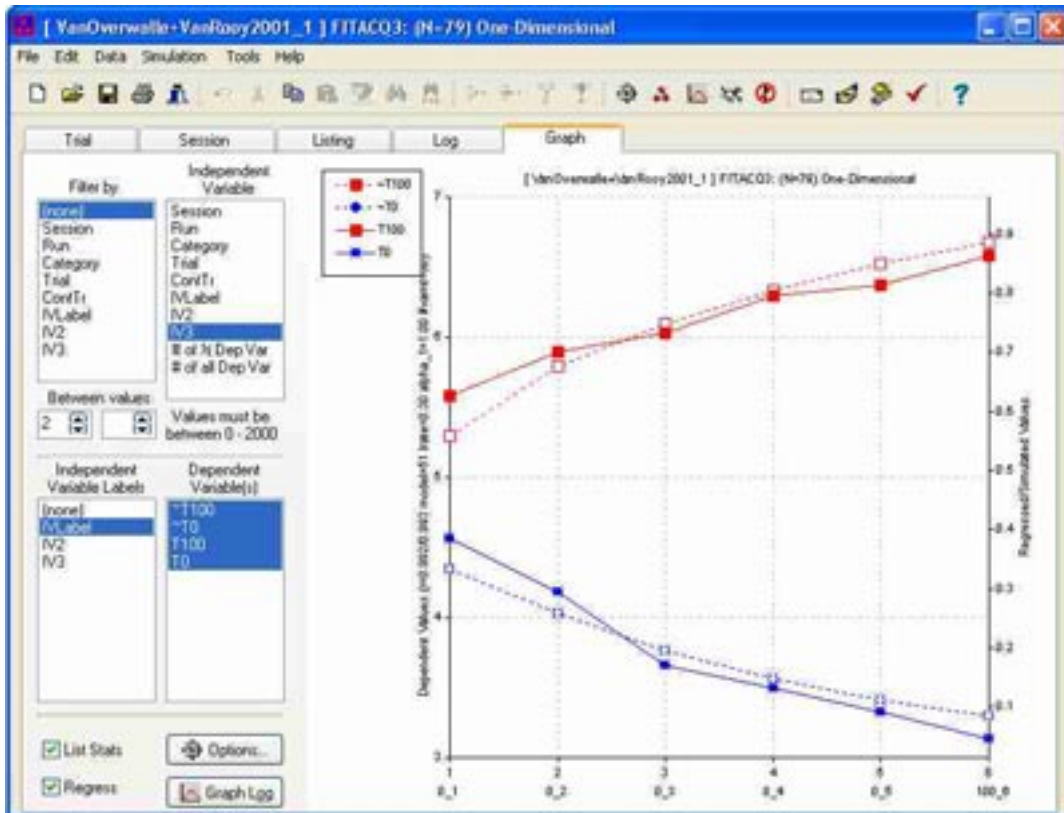


Figure: screenshot of our Fit2 software for the connectionist simulation of cognitive phenomena

type of simulation allows us to study the interaction between connectionist learning processes on two levels: within individual agents and between the agents.

7.3. Observation

The disadvantage of simulations is that they still are based on a very simplified model of reality, which is wholly dependent on the subjective assumptions of the designer. Therefore, many simulations have been criticized for merely confirming the biases of their creators. Real-life observations of actual social systems, as used in the distributed cognition tradition [Hutchins, 1995], can evade these criticisms, by providing an open-ended source of unanticipated effects and interactions. The disadvantage is that they are very time-consuming and difficult to control so that only a few variations of a basic situation can be investigated.

We therefore wish to combine the benefits of both methodologies, using observation to suggest new hypotheses and simulation to quickly explore the different implications of these hypotheses, so that the most promising ones can become the focus of a new observation. Moreover, the results from the observations can be used to adjust the parameters of the simulation, as we have frequently done with our connectionist simulations of individual and group cognitive processes [e.g. **Van Rooy, Van Overwalle, Vanhoomissen** et al., 2003; **Van Overwalle, Heylighen & Heath**, 2005]. Conversely, since the simulation can be run with many different rules and initial conditions, this may allow us to find the most interesting cases (e.g. that demarcate different models), which we can then try to replicate empirically.

There are two basic methods of empirical data gathering relevant for distributed cognition research: *experiments*, in which the set-up is explicitly manipulated by the researcher to control for specific variables, and *ethnographic observations* or *case-studies*, in which the researcher investigates an existing system, trying to interfere as little as possible, while noting down all observed phenomena. The former methodology is most common in psychology, the latter in cognitive anthropology [e.g. Hutchins, 1995] and organizational studies. Our group has experience with both approaches, especially with laboratory experiments [e.g. **Van Overwalle, Heylighen** et al., 1992, Jordens & **Van Overwalle**, 2001; **Van Overwalle & Van Rooy**, 2001a, b; **Van Overwalle**, Drenth & Marsman, 1999], but also with video recording and content analysis of group problem solving sessions, and the statistical analysis of existing linguistic corpora (e.g. recordings of conversations [**Heylighen & Dewaele**, 2002], or virus hoaxes [**Chielens**, 2003]).

Compared to “field” observations, experiments provide more explicit control over different conditions, so that they allow us to test and compare different models more precisely. However, by creating an artificial, researcher-designed situation, they may ignore real-world, “wild” phenomena [Hutchins, 1995]. As such, experiments can fill the gap between the open-ended but difficult to control field observations and the “closed” computer simulations. We will now propose two experimental paradigms that try to combine the advantages of both approaches in investigating distributed cognition.

7.4. Group Communication Experiments

The more traditional psychological experiments where individual participants are subjected to controlled stimuli (e.g. flashes of light, or reading a text) after which their reactions are registered (e.g. by letting them fill in a questionnaire concerning their experience/ interpretation) appear ill-suited for observing distributed cognitive processes, since these essentially occur *between* participants. However, such interaction between subjects is increasingly being studied through *group experiments* where members of a group work towards a common goal, or observe the same stimuli, after which the individual (private) or group (public) reaction is measured. An example particularly relevant to our project is the research of Garrod [1998; Garrod & Doherty, 1994] on how groups coordinate the concepts and rules they use when collectively tackling a problem.

To test hypotheses concerning group interaction, we can focus on minute details of the interaction between participants, extending earlier research on the individual’s reaction to private stimuli into the realm of group input. Alternatively, at the group level, we can explore how controlled information may be shared or become distorted during the communication or discussion in a group.

For this latter type of experiments, social psychologists have used two basic paradigms that reflect alternative ways in which information is propagated between people: *parallel* and *serial* communication. In a parallel communication design, the information is spread from all communicators directly to each participant, like in a group discussion. Thus, the participant has direct access to the observations and impressions of all the people who received the stimuli. In a serial reproduction design, the communication of information is passed sequentially from person to person, like in rumors and gossip. The first communicator in the chain receives the information, memorizes it, and then communicates this information to the second person in the chain, and so on. Here we can investigate how the information changes as it progresses through the chain, depending on factors such as the background knowledge that the participants have [e.g. Lyons & Kashima, 2003].

7.5. *Computer-mediated games*

A related experimental paradigm, inspired by MAS, experimental economics, and studies of group dynamics, may provide us with a direct bridge between empirical and simulation methods. Most MAS and economics experiments have the structure of a “game” where agents (people or software agents) interact by making “moves” towards their partners, following certain imposed constraints or rules, while trying to achieve an individual or collective goal (e.g. maximizing their utility).

Usually, these games (e.g. the ubiquitous Prisoners’ Dilemma game) are rigidly constrained, leaving the agents very little freedom in choosing what move to make (e.g. either “cooperate” or “defect”). This creates a highly artificial situation whose relevance to real-world phenomena is limited. However, this does not need to be the case, as we can conceive a continuum of game situations, from completely controlled to almost completely free-form and spontaneous. Free-form games (e.g. unconstrained brainstorming sessions) may attract our attention to unanticipated phenomena, while more constrained games allow us to test specific hypotheses and compare different models or parameter values.

Still, even free, open-ended games can give us accurate control over data collection. Suppose we let the participants interact through a computer-supported medium that offers them a choice of moves. The computer system registers which moves were made by whom at what moment, providing the experimenter with precise, easily analyzable data. For example, the system may support a group discussion by allowing the participants to submit specific types of contributions: propositions, questions, confirmations, refutations, evaluations, etc. However, the system should also allow completely free-form, unconstrained interactions (e.g. spoken and non-verbal communication) that can be recorded on video for content analysis, so as not to artificially restrict expression.

Such a group discussion does not need to be limited to experimenter-defined topics or formats, but can include real-world activities, such as the scientific discussions that form the basis of the Principia Cybernetica Project [Heylighen, 2000]. In this case, the observers do not control the topic, participants or dynamics of the discussion, but merely offer tools to assist the participants in their spontaneous interactions, while using those tools to accurately register what happens.

The advantage of the more constrained computer-mediated games, on the other hand, is that they lend themselves to direct comparison with multi-agent simulations. For the more rigidly defined games (such as the Prisoners’ Dilemma) it is easy to run the same game with software agents and human subjects, so that the similarities and differences between simulation and reality can be evaluated numerically.

8. **Concrete subprojects**

We will now show how these methodologies can be applied to elaborate and test each of the five basic assumptions (sections 6.1 - 6.5) that form the backbone of our proposal. This defines five concrete subprojects within our overall project for the development of an integrated theory of distributed cognition.

8.1. *Groups of agents self-organize*

While all dynamical systems will eventually “self-organize” (reach an attractor) by definition [Ashby, 1962], the concrete question we must address is how and under what conditions a group of agents will self-organize, and what kind of cognitive or social structures will emerge from their interactions. Given the complexity of this process, and the many steps that can be expected to be necessary in order to see

non-trivial structures emerge, this working hypothesis is best tested first through an agent-based computer simulation, which can then be compared with an experiment involving human subjects.

8.1.1. Learning to cooperate and trust

To build the first simulation, we plan to start from the KEBA (Knowledge Emerging from Behavior) system that we have developed earlier [Gershenson, 2002]. This is a 3D, virtual environment where agents interact with each other and with external objects, while their actions can be “rewarded” (reinforced) or “punished” (inhibited) depending on the benefits they bring to the agents. For example, it is to the benefit of an agent to find sufficient food and water, and to avoid predators and obstacles in its environment. By experimenting with different rules to guide agent behavior [Gershenson, 2003, 2004], we expect to create a self-organizing dynamics, in which the agents come to cooperate in a coordinated system.

We start with a group of agents that are individually recognizable by “tags” or “markers” [cf. Riolo, Cohen & Axelrod, 2001; Hales & Edmonds, 2003]. The agents interact according to a game protocol with the following moves: an agent makes a request towards another agent and the other one either responds appropriately or not. Agents learn from these interactions in the following manner: if the result is positive, the agent will get more *trust* in the other agent’s cooperativeness. Thus, the probability increases that it will make further requests to that agent in the future, or react positively to the other’s requests. Vice-versa, a negative result will lead to more “distrust” and a reduced probability to make or accept requests to/from this agent.

Still, to recognise this agent, it has to take its clue from the tag, which is in general not uniquely identifiable. This means that a later interaction may be initiated with a different agent that carries a similar tag, but that is not necessarily willing to cooperate to the same extent. We may assume that if the first few interactions with agents having similar tags all generate positive (negative) results, the agent will develop a default propensity to always react positively (negatively) to agents characterised by that type of markers, while, vice-versa, the others will learn to react in the same way to the first agent.

We expect that in this way, through positive feedback, the initially undirected interactions will differentiate into a structured network of cooperative relations, in which agents with certain tags preferentially interact with agents with certain (similar or different) tags, while avoiding to interact with others. The tags and their learned associations thus develop the function of a distributed *mediator* [Heylighen, 2004] that increases the probability of positive interactions by creating a social network and a differentiation between “friends” and “strangers”.

8.1.2. Learning to coordinate and divide labor

In the next simulation we try to evolve a mediator that provides the group with a form of distributed cognition, i.e. an organization that allows the agents to collectively solve problems that are too complex to be tackled individually. These problems are represented as a complex of tasks. The tasks are mutually dependent in the sense that a certain task or certain tasks have to be completed before another task can be initiated. Each agent can either execute a task itself, or pass it on (*delegate*) to another agent.

Initially all agents are equally competent or incompetent, meaning that they have the same probability of successfully accomplishing a task. However, each time it accomplishes a task, an agent becomes more “experienced” so that the probability increases that it will bring the same task to a successful end later on. We moreover assume that the agent who delegated a task will increase its trust in the competence of the agent that accomplished that task, and thus increase its probability to delegate a similar task to the same agent in the future. Otherwise, it

will reduce its trust. As demonstrated by the simulation of [Gaines, 1994], this assumption is sufficient to evolve a self-reinforcing division of labour where tasks are delegated to the most “expert” agents.

However, when the tasks are mutually dependent, selecting the right specialist to carry out a task is not sufficient: First the prerequisite tasks have to be done by the right agents, in the right order. When the agents do not know a priori what the right order is, they can randomly attempt to execute or delegate a task, and, if this fails, pick out another task. Eventually they will find a task they can execute, either because it requires no preparation, or because a prerequisite task has already been done by another agent. In this way the overall problem will eventually be solved. In each problem cycle, agents will learn better when to take on which task by themselves, or when to delegate it to a specific other agent. That is, they will eventually develop clear connective rules of the form:

IF confronted with task of type A
THEN tackle it through action B, or:
 pass it on to agent with tag X.

We expect that this learned organisation will eventually stabilise into a system of efficient, coordinated actions, adapted to the task structure. While no single agent knows how to tackle the entire problem, the knowledge has been *distributed* across the system, by means of the learned associations between a tag or agent and the competence for a particular task.

For both simulations our research will consist in registering and analysing the dynamics of the process of social organization as accurately as possible, by comparing the structures that emerge during the different stages of the process. In addition, different variations of the model will be tested, inspired by alternative theoretical hypotheses coming from the literature or from our own research, and by the results of preceding simulations. Specific properties that will be varied are the numbers of agents, forms of interaction (cooperation, indifference and/or conflict), strength and dynamics of trust relationships, task structure (complexity, mutual dependency), and tag distributions (fixed or variable, random or dependent on previous interactions, more or less homogeneous). This will allow us to better understand which factors contribute to an efficient organisation, and which will rather increase the risk of conflicts, fragmentation, or prejudice.

8.1.3. Comparing simulated with real agents

In a second stage, assuming we have developed a successful MAS model for the self-organization of distributed problem-solving, we can try to test it further with an experiment involving a group of real subjects, who are given a complex of tasks together with “rules of the game” that are abstracted from our simulation. This will allow us to check whether the model has not overlooked any features of human interaction that essentially affect the self-organizing dynamics.

A simple, yet concrete, paradigm for this is a computer-mediated “management game” [cf. Rulke & Galaskiewicz, 2000] where the participants are confronted with a number of complex, changeful and mutually dependent tasks, such as the management of a simulated company or city. There exist many such computer games, inspired by the classic ‘SimCity’. The ideal environment needs to be complex enough to promote specialization or division of labor between the participants and to discourage non-directed communication so as to avoid information overload. Moreover, it must allow easy manipulation of the connections between participants, so that we can control who communicates with whom.

We will first run the experiment with fixed network structures that already have been tested as to their effectivity [Bavelas, 1950; Guetzkow & Simon, 1955], such as the centralized “hub and spokes”, “circle”, and “all channel” where everyone is connected with everyone. This will allow us to determine the base level performance of groups that use this platform. If our hypotheses are correct, however, a learning network should be more effective than any rigid structure. In the next stage, we will therefore make the network self-organizing. We will start with the most successful of the fixed structures and let it evolve according to the learning algorithms that were most successful in the computer simulations, so as to check whether this leads to a further improvement of the group performance.

To test the full power of self-organization, we will then start the experiment with a random network where every participant is able to communicate with 3 or 4 others, and then allow the learning rules to create new connections. We expect that even in such a totally unstructured situation the system will discover more effective connections and thus generate a network adapted to the specific group and problem situation. (If it does not, it means that at least one of our basic assumptions is falsified, and that they will have to be changed or extended).

Another question then arises: in what way does this self-organized structure differ from or compare with traditional organizational structures [cf. Ahuja & Carley, 1999] and the structures found in our multi-agent simulations? And which are the factors that make a certain structure more or less efficient in tackling the problem situation? To be able to answer these questions we will carefully register and analyse all the steps in the process and use speech protocols and interviews of the subjects to determine which implicit factors may have caused them to communicate more with certain people about certain tasks.

8.2. The organization co-opts external media for information sharing

To test and elaborate our second assumption, we need to extend our MAS with a physical environment containing virtual “objects” that can be used to permanently or temporarily store information, and thus potentially form a medium for communication between the agents. This implies that an agent should be able to change the state of an object, so that it can leave tags or markers in its environment that may later be interpreted as a signal by the same or other agents. However, if we want to understand the *self-organization* of media use, we should not assume a priori that the tags have a cognitive or communicative function. Initially, they should be seen as not more than “side effects” of the agents’ actions—the way the erosion of a path is a side effect of frequent walking.

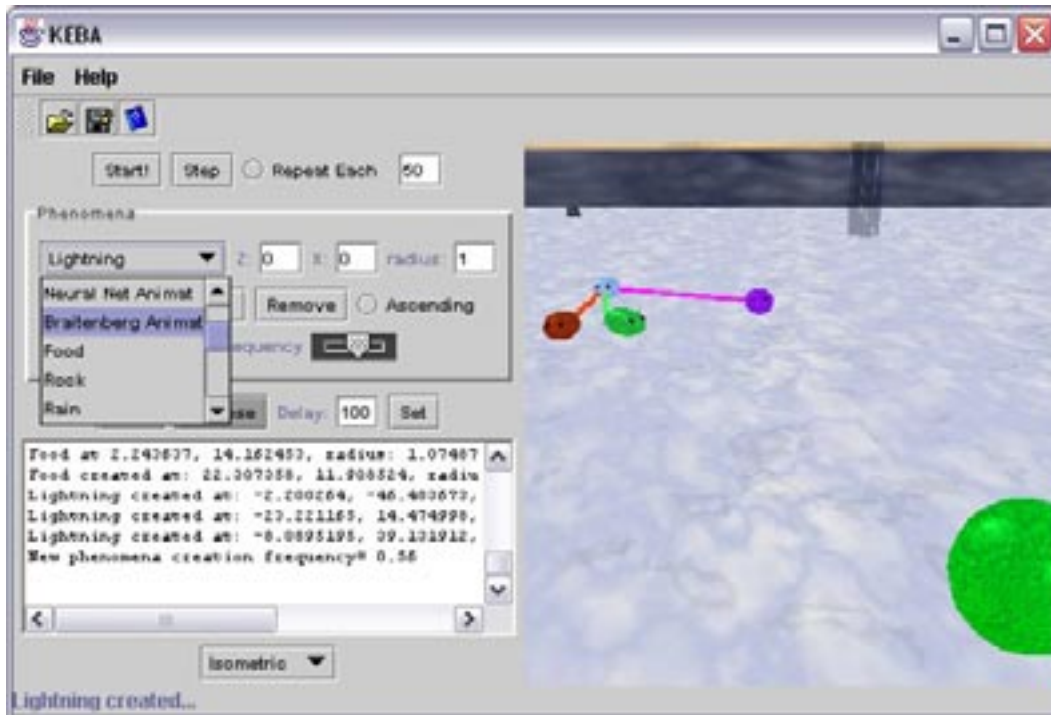


Fig.: a screenshot from the KEBA simulation environment, showing some of the animats (right), and on the left the controls to manipulate their behavior, learning mode and environment

This can be achieved by having all agent actions (e.g. moving, eating, drinking, ...) leave some kind of *traces* in the shared environment. Some of these traces will be indicative of important phenomena (e.g. the proximity of food), others not. Some of the traces may remain for a long time, others will quickly be erased by changes in the environment or other agent activities. Like in the original KEBA simulation [Gershenson, 2002b], we assume that agents can perceive basic features of their environment (including other agents' traces), and that they learn to associate these features with other features and with their in-built goals (e.g. finding food), using classic connectionist or reinforcement learning algorithms. They thus will learn to recognize which traces provide useful information about the phenomena that are important to them (e.g. food).

There seem to be two basic possibilities:

- 1) The trace is useful to the agent that perceives it (e.g. pointing a predator towards its prey), but detrimental to the one that made it (e.g. making the prey more visible for the predator). In that case we can expect an arms-race type of evolution, in which "predators" become better at detecting traces, while "prey" agents become better at hiding their traces. This is unlikely to lead to any kind of shared medium.
- 2) The trace is useful to both parties (for example because it indicates a shared danger). In this case, there will be a selective pressure for both parties to make the trace easier to perceive, by becoming more adept at leaving clear, stable and informative traces and at distinguishing and interpreting traces left by others. Thus, the trace will co-evolve with the agents' cognitive abilities, to become an efficient, shared communication medium that allows one agent to leave messages for itself and others.

To explore the ramifications of this simple model, we need to combine it with the previous simulation models in which agents learn to cooperate and coordinate. Clearly, the more efficient the pattern of cooperation that has evolved, the more useful shared media can become, and therefore the stronger the selective pressure to produce and interpret traces. Vice-versa, the better the quality of the available media, the easier it will be to evolve a sophisticated cooperative organization. Thus, we can expect that an integration of the tracing model with the self-organization model will evolve more quickly than either simulation on its own. By varying the different parameters of the model (e.g. durability of traces, sensitivity of the environment to agent activities, and sensitivity of agents to environmental features), we can try to determine the optimal combination for efficiently evolving a distributed cognitive system.

The tracing simulation unfortunately does not have an obvious analogue in human experiments, since people already start out with strong preconceptions about what constitutes a meaningful signal, and thus are unlikely to pay much attention to mere “side effects” of other people’s activities (at least in the time span of a typical experiment). A more realistic set-up may offer participants the choice between direct communication (e.g. talking) and the use of one or more indirect media (e.g. paper to jot down notes, or a shared “blackboard” on a computer system). Some media may be more helpful for certain interactions (e.g. paper to draw diagrams), and other media for others (e.g. talking to express emotions). By giving the group a complex task that requires different kinds of cognitive and communicative actions, we provide an incentive for them to self-organize, and create a division of labour—not only between individuals, but between media.

A review of the literature, theoretical analysis and the tracing simulation may give us some hints on the features of tasks and media (e.g. reliability of storage, ease of changing, ease of sharing...) that determine which kind of medium will preferentially be used for which kind of task, and how this will influence the efficiency of the distributed cognitive process. Experiments will then allow us to test these hypotheses. Moreover, we can repeat the same experiment with and without external media, to check in how far media use makes the group more effective in solving the problems posed to it. These experiments are quite innovative in psychology, where the role of media in group decision and action has rarely been studied. The approach can also be extended and embedded in the group communication experiments described in sections 8.1 and 8.4.

8.3. *distributed cognitive systems function like connectionist networks*

While the previous MAS models focus on the concrete *behavior* of agents, they pay little attention to the specific information transmitted between members of a group. While this is a desirable characteristic to model the beginning stages of social self-organization in animal and human evolution, among adults collaboration is usually supported by intelligent conversation that does not focus just on behavior, but on the exchange of abstract ideas and opinions in order to coordinate collective beliefs. These collective beliefs may not have immediate implications for action, but may later on support group decisions.

To model the communication of ideas and beliefs, we make use of a standard connectionist modeling approach that has served us well in the past to model the development of individual impressions, opinions and beliefs, and will extend this for a communication setting in which several individuals exchange their beliefs. We will base this approach on a standard recurrent connectionist network, which is distinguished by (a) its architecture, (b) the manner in which information is processed and (c) its learning algorithm.

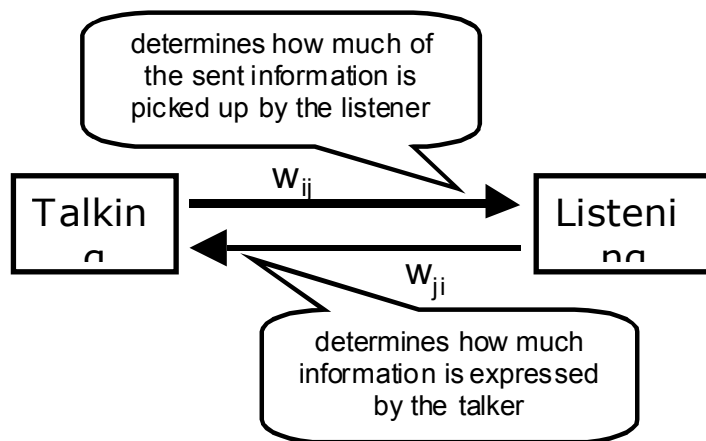


Figure : The role of trust weights in communication between agents.

- (a) In a recurrent architecture, all nodes within an agent are interconnected with all of the other nodes of the same agent. Thus, all nodes send out and receive activation.
- (b) Received information is represented by *external activation*, which is automatically spread among all interconnected nodes within an agent in proportion to the weights of their interconnections. The activation coming from the other nodes within an agent is called the *internal activation*.
- (c) The short-term activations are stored in long-term *weight changes* of the connections; these are driven by the difference between the internal activation received from other nodes in the network and the external activation received from outside sources.

This model for the cognitive processes within an agent can now be extended to communication between agents [Van Overwalle, Heylighen & Heath, 2005], under the assumption that information is represented in broadly the same manner in different agents. Communication is represented by transferring the activation of nodes from “talking” agents to “listening” agents. This is accomplished by activation spreading between agents in much the same way as activation spreading within the mind of a single agent, with the restriction that activation spreading between agents is (a) limited to nodes representing identical attributes and (b) in proportion to the connection weights linking the attributes between agents.

A crucial aspect of this between-agents dissemination of information is *trust*, or the degree to which the information on a given attribute or concept by a given agent is deemed reliable and valid. Because agents can play the role of speaker or listener, the trust connections in the model go in two directions for each agent: Sending connections for a speaking agent and receiving connections for a listening agent.

Communication is more effective if the information is believed to be trustworthy. This is implemented in the trust connection w_{ij} from an agent i expressing its ideas to the receiving agent j (see Fig.). When trust is maximal (+1), the information expressed by the talking agent is accepted as such by the listening agent. When trust is lower, information processing by the listener is attenuated in proportion to the trust weight. When trust is minimal (0), no information is processed by the listening agent. Thus, the listener sums all information received

from talking agents in proportion to the respective trust weights, and then processes this information internally.

The criterion of *novelty* (section 6.4) suggests that communicators transmit only information that adds to the audience's knowledge. On the other hand, research on group minority suggests that communicators tend to increase their interaction with an audience that does not agree with their position. This is implemented in the model by the trust weights w_{ji} from the listening agent j to the talking agent i (see Fig.). These weights are the result of earlier communications in which the listening agent expressed judgments on an issue that were congruent with the talking agent's knowledge. When these trust weights are high, consensual knowledge on an issue is assumed and the talking agent will refrain from expressing these ideas further. In contrast, when these weights are low, the talking agent tends to express its ideas on this issue more strongly, as if to compensate for the expected attenuation of the message by a sceptical receiver.

Like in the standard delta learning algorithm which is used to adjust memory traces within individual agents, the degree of trust depends on the error between external beliefs expressed by a talking agent and a listening agent's own internal beliefs. If the error is below some *trust threshold*, the trust weight between the concepts held by the two agents is increased towards 1; otherwise, the trust weight is decreased towards 0.

A distributed cognitive process is initiated when one or more agents receive one or more pieces of external information. These pieces of information may complement or confirm each other, or they may be inconsistent. The agents propagate their interpretation to "listening" agents, according to the trust connections. A listening agent will aggregate and process the information it receives from one or more talking agents. It will then pass on its own interpretation, taking into account the knowledge stored in its internal connectionist network that is the result of previous learning episodes, to others. These will again transmit their own interpretation of all the information received, in parallel or in sequence, to the other agents, and so on.

At each transmission stage, the pattern of spreading activation undergoes a transformation determined by the connection pattern within and between agents, during which some information is irreversibly lost, until the connectionist network settles into an attractor. This equilibrium activation can be seen as the final, collective interpretation of the externally received information.

Using this computer model, we will try to replicate a variety of basic empirical findings from the psychological literature on group persuasion and communication. Successful replication of the general trends will provide a strong confirmation of our connectionist model; failure to replicate well-known facts will be a strong indication that the model, if not falsified, at least lacks some essential features. Some of the specific group phenomena that we want to simulate are:

- Referencing of concrete and abstract objects during communication, and how that affects what and how much we talk to describe them [Krauss & Weinheimer, 1964; Schober & Clark, 1989; Steels, 1999]
- The communication of information about group members and how that may enhance or decrease stereotypes [Lyons & Kashima, 1993; Brauer et al., 2001; Klein et al., 2005].
- Group conformity and polarization that leads the group to take more extreme positions [Ebbesen & Bowers, 1974; Mackie & Cooper, 1984; Isenberg, 1986]
- Insufficient sharing of unique information so that not all resources of a group are employed [Larson et al., 1996, 1998; Stasser, 1999; Wittenbaum & Bowman, 2003]

- Learning of relevant information channels and trustworthy sources in social networks so that available but dormant information is exploited more efficiently [e.g., Leavitt, 1951; Mackenzie, 1976; Shaw, 1964].

In addition to this attempt to replicate known experimental results, we will use the simulation environment to investigate the effects of parameters such as the number of agents, the number of nodes per agent, the amount of consistent or inconsistent information that is provided as input to the system, the distribution of this information over the agents (e.g. information can be given to one or a few agents at a time, or to the whole group) and over time. These simulations should give us more insight in the main factors determining the selectivity of information processing (see section 6.4), that form the focus of the next subproject (8.4).

Ultimately, we will attempt to integrate the different simulation approaches (8.1.1, 8.1.2, 8.2 and 8.3) in a single model of collective action (MAS and media), communication (connectionist trust model), and cognition. We believe that such combined model will have the most power to describe and accurately predict the different aspects of distributed cognition that we study in this project.

8.4. information in the network is propagated selectively

At all levels of communication, from the basic level of animals sharing traces to more abstract information exchange between humans, we expect information propagation to be selective, being shaped by the needs and goals of individuals and collective. However, before assuming that this selection is *a priori* goal-directed, we have to ask the question to what extent information propagation between humans is selective simply because of inherent features of the act of communication itself. In this respect, the interpersonal distribution of information is crucial.

Of the many factors that impact on group biases, we consider the *trustworthiness* of (the information provided by) the communicators as theoretically most crucial in this interpersonal context. In addition, the aforementioned criteria of *utility*, *novelty*, *consistency*, *simplicity*, *expressivity* and *conformity* can be explored to check in how far they affect the propagation of information during communication.

From previous simulations [Van Overwalle, Heylighen & Heath, 2005; Van Rooy, Van Overwalle et al., 2003] and prior experiments [e.g., Lyons & Kashima, 2003], we expect that in general group impressions will become increasingly stereotypical while they are communicated by more communicators in parallel (e.g., free discussion), or further down along the communication chain, as the elements of the message that appear irrelevant, inconsistent, non-conformist, difficult to express, or too complex are filtered out. However, under some circumstances, e.g. when the non-stereotypical information is very novel or valuable, we may expect the opposite to occur. The connectionist model described in the previous section predicts that the development and deployment of trust weights will strongly affect how opinions and beliefs are propagated in the collective.

Although there is increasing awareness that trust is an important "core motive" in human interaction [Fiske, 2005] and while its neurological underpinnings are gradually unveiled [King-Casas et al., 2005], there has been little empirical study of trust in social cognition, let alone on its specific role in human communication and information exchange. The same is true for novelty, although we will focus our research effort predominantly on trust, as this core aspects seems to be most fundamental and neurologically grounded.

Several research strategies and designs are possible. One can explore how humans themselves perceive trust, how trust influences information exchange and

what the antecedents are that determine whether trust is high or low. Moreover, one can study to what extent trust is working at the implicit (i.e. automatic) or explicit level. The same designs can be used for novelty. We will discuss each of these approaches in turn. Note that the experiments described below will be conducted with approximately 60 participants or 15 groups of 4 members each.

8.4.1. Antecedents of Trust

Which factors increase or decrease trust in information provided by other actors? This is the most crucial test of the MAS connectionist model. Indeed, the model proposes that if no a priori expectations about the sender exist, people will trust information so long as it *fits with their own beliefs*. Although some degree of divergence is tolerated, if the discrepancy is too high, the information will not be trusted and hence not influence people's own belief system. Thus, rather than some internal inconsistency or ambiguity in the story told, it is the *inconsistency* with one's own beliefs that sets off the listener and make him or her distrust the information.

These opposing predictions can be easily tested empirically, by providing information that varies (a) in the degree of internal inconsistency or ambiguity, and (b) in the degree of inconsistency with prior beliefs. This latter aspect can either be manipulated experimentally by providing the participants with background information on the topic, or by measuring their existing beliefs and making up information that is inconsistent with it.

8.4.2. Consequences of Trust

Although consequences of (dis)trust cannot be explored without having some idea of how to manipulate or change perceived trustworthiness, for explanatory sake, we will first discuss the consequences of trust (as it provides a way of measuring its effect) and then turn to several ways of manipulating trust. This can be examined in discussions of groups (or dyads), by exploring how much of the information provided to the other actors is taken into account. In general, the MAS connectionist model predicts that more trust will result in stronger change of beliefs and stronger adoption of collective views and solutions.

There are several ways to explore the extent to which (dis)trusted information influences one's beliefs. This can be measured (a) directly, by *asking* participants at the end of a discussion how much they thought the information provided by some agents was useful, how much they privately believe the consensus that was reached (when the task involves a collective decision) or how much they agree with the group solution (when the task is to find a solution to a problem). (b) More indirectly, one can measure the *time* it took to reach a consensus or a solution in the group, under conditions of trust or distrust. Other related measures are (c) how often there was expression of *disagreement* in the group, opposition or denigration of others, and so on. In addition, we can explore (d) to what degree the quality of the decision (e.g., consensus or shared understanding reached) can be predicted on the basis of indices of trust or other process variables. For this question to be answered, we videotape on-going discussions. Since groups obviously will differ in the amount of shared understanding or consensus on an issue, we can explore whether the variability in the outcomes of these groups can be predicted by some process variables related to trust (or perhaps totally unrelated to trust) observed in the videotapes.

In more controlled laboratory conditions, the consequences of trust can be measured by (e) the response time in answering questions about the information given by some actors. The prediction is that participants will agree less with information from an untrustworthy source, and that it will take them more time to read and understand it.

Finally, one can make *novel predictions* about the consequences of trust that rely on (f) earlier research findings and / or on (g) model simulations. For instance,

one specific prediction made by the model is that there will be more sharing of information uniquely held by members of a group [cf. Stasser, 1999] if the members of the group trust each other more rather than less.

8.4.3. Manipulation of Trust

The foregoing predictions are based on the idea that trust can be manipulated. One way to do this is to vary the reported trust in the agents, or the information they provide. This can be done rather *blatantly*, (a) by providing verbal information on the trustworthiness of the information given by some communicators in a group discussion or task, (b) by varying prior expectations about the communicators, or (c) by varying whether the communicators are member of some rival groups or not, and so on.

More implicit vehicles of trust manipulation might be (d) nonverbal *facial expressions* of disbelief, or other nonverbal expressions of unease and untrustworthiness. The literature on emotions provides as yet little evidence on pancultural facial expressions of distrust, but it seems to us that a facial expression of disbelief might strongly affect people's impression of the trustworthiness of information. In the Social Cognition Lab, we have extensive experience with the presentation of subliminal presentation (below awareness) of facial expressions. At presentation times outside the focus of vision that are too short to be consciously seen, for instance, it is possible to influence one's self-esteem by the mere subliminal presentation of happy and sad faces. We hypothesize that the subliminal presentation of faces expressing disbelief (while an auditory message is presented) might result in less trust of that information, even when participants are unaware of the influence of this contextual factor.

8.4.4. The Automaticity of Trust

Our simulations lead us to expect that trust between individuals is developed and applied automatically, outside of consciousness, rather than being a deliberate, controlled process. In contrast, although automatic to some degree, we expect that other criteria such as novelty and attenuation of talking about known information can be more easily overruled by controlled processes, such as task instructions and goals, since the act of speaking itself is largely within the control of the individual.

To test that the use of trust is automatic, we can make use of an experimental paradigm on spontaneous inferences that our research group has used before [Van Overwalle, Drenth & Marsman, 1999]. In short, in these experiments we will compare statements by trusted and distrusted sources, and see to what extent their information is spontaneously integrated in the inferences about the target. For instance, we can provide information implying some trait about the actor (e.g., the sentence "Jane solved the mystery halfway the book" implies that Jane is intelligent), and see to what extent this trait is also spontaneously believed by the receiving individual. We expect that this will be more the case for trusted sources than for distrusted sources, demonstrating that trust is automatically applied.

Similarly, the model assumes that to some degree, speakers will spontaneously refrain from telling information that the listener already knows (the novelty criterion). We can test this by using a paradigm in which spontaneous thoughts on novel versus old story elements are measured in the same manner as above [Van Overwalle, Drenth & Marsman, 1999]. For instance, we ask our participants to communicate a specific story to someone else who either does or does not possess the same background information. Immediately after the communication instruction or after telling the story, we can measure how spontaneously participants think about novel information rather than known or consistent information.

8.5. novel knowledge emerges

To elaborate and test our final hypothesis—that distributed cognitive systems are able to produce qualitatively new knowledge structures—we could use the integrated MAS connectionist simulation coming out of the first three subprojects to check in how far it produces novel concepts and relations between concepts. However, since this is the hypothesis where potentially we can expect the biggest surprises, we prefer to start with an open-ended observation of real group processes, so that it can give us a better idea of what kind of novelty can actually appear, and which factors stimulate or inhibit this form of “social construction”, “collective creativity” or “distributed imagination”.

To allow a quantitative analysis of our observations, we propose the following simple operationalization of knowledge creation. First, we operationalize a concept as a process of categorization, whereby different phenomena are classified as instances of this concept to a greater or lesser degree. The colour of blood, for example, may be classified with certainty (strength 1) as “red”; that of a brick with strength 0.7; that of an orange with strength 0.3; that of grass with 0. A concept can thus be represented as a vector, e.g. (1, 0.7, 0.3, 0), the components of which correspond to the categorisation strengths. Such representations in multidimensional vector spaces have proven their usefulness in the semantic analysis of concepts [Heylighen, 2001b; Foltz, 1996]. Then we operationalize a connection between concepts as the subjective probability or expectancy of category *B* (e.g. the phenomenon is *yellow*), given category *A* (e.g. the phenomenon is a *banana*). This determines a matrix of cross-associations between concepts [Heylighen, 2001b].

We can now apply these measures at both the individual and group level. For each participant, each concept is represented by a vector. The comparison of the vectors for different individuals in the group gives us an objective measure for the spread or diversity in the initial viewpoints. The average of all individual vectors defines the “collective” concept for the group [Heylighen, 1999]. Similarly, the average of expectancy values for connection strengths determines the collective association between concepts [cf. Bollen, 2001, 2000; Heylighen & Bollen, 2002]. After the participants have interacted, individual and collective concepts and connections can be measured again.

By comparing the results before and after the group discussion, we can numerically estimate the cognitive changes that occurred in the group. These changes can further be visualized by performing a principal components analysis on the data to reduce the number of dimensions of the vector space to 2 or 3. We can then represent the different individual and collective concepts in this abstracted space before and after the group discussion, so that we get an immediate intuitive view of how they have shifted.

Starting from our general assumptions we expect the following to hold true:

- 1) the spread among the participants will diminish (i.e. individual concepts will become more clustered), as exchange of information between individuals strengthens consensus;
- 2) the collective concept will undergo a non-linear transformation, meaning that it is no longer a linear combination of the original individual concepts:
 - a) we expect that in general vector components about which there was a relative agreement will be strengthened because of conformity pressure, while components important to only one or a few individuals are suppressed, or disappear altogether; if some of the members of the group have a higher authority (trustworthiness) than others, their views will carry a proportionately higher weight in the eventual consensus.
 - b) however, if during the discussion a novel or minority interpretation is produced that scores significantly better on one or more of the other selection criteria (simpler, more coherent, more useful, ...) this may push

the dynamics into a different attractor, strengthening vector components that didn't have strong values in any of the individual concepts.

These hypotheses will be tested and developed into a more detailed model by investigating the factors that control the process. At least the following factors are likely to be relevant: *diversity* in views among the participants, *uniqueness* of their perspectives, type of *interaction*, *complexity* or *ambiguity* of the concepts. A better understanding of these elements and their causal effect will allow us to choose them in such a way as to maximise the quality of the consensual concept.

In our basic set-up, a small group (about 10) of experimental participants are requested to discuss a given concept, with the objective of achieving a shared understanding. The concept is chosen such that everyone has some experience with it, but there remains sufficient vagueness or ambiguity to allow different interpretations. The participants are informed about the concept before the experiment, so that they can prepare their thoughts without mutually influencing each other. They are asked in particular to suggest for the concept (e.g. *fruit*) a number of examples (e.g. *apple*), counterexamples (e.g. *potato*) and intermediate cases (e.g. *pumpkin*) of the category. We select the most representative ones of those, and submit the resulting list of some thirty items to all participants. We ask them to score each one on a 10-point scale, indicating the degree to which they consider it to belong to the category. This produces the initial concept vectors for all participants.

In the group discussion, each participant starts with a short description of what the concept means for him or her, and then is allowed to reply to the interpretations of others, using examples, arguments and counterarguments. After a period long enough to allow each participant to intervene several times, the discussion is stopped, and the concept vectors are measured again. The statistical comparison of initial and final vectors provides us with a quantitative analysis of the evolution of the concept. An example of novelty creation would be that after discussing it the group concludes that a *tomato* is a *fruit*, even though initially none of the participants considered it to belong to that category. A content analysis of the different interventions provides us with a more qualitative picture of the arguments and factors that have influenced the outcome. The discussion is recorded on videotape, and analysed for specific factors that appear to have influenced the outcome. The possible reasons why a particular participant has or has not changed positions are explored by focused interviews.

Complementary to this controlled experiment, we will also observe a "wild" type of discussion, using computer-mediation to record accurate data. The goal of the Principia Cybernetica Project [Heylighen, 2000; Heylighen & Joslyn, 1993] is to let a variety of experts develop a consensual theoretical framework by means of computer-supported discussion of concepts and principles. This discussion has been on-going since 1991 using electronic mail discussion lists, face-to-face meetings, and the web [Heylighen, Joslyn & Turchin, 1993-2004]. There is plenty of textual material available recording past discussions, which can be analysed to look for the novelty-creating processes that we hypothesize. Moreover, by providing the participants with a more structured computer-mediation, such as the CLAIMAKER argumentation environment developed by a group associated with Principia Cybernetica [Shum et al., 2003], we can accurately register the different "moves" in future, open-ended discussions within the group. By moreover asking participants to score the connections between the concepts that are likely to be discussed before and after the extended discussion (which can last months), we get a quantitative measure of the changes.

9. Deliverables

In addition to the novel insights and conceptual framework, we expect this project to deliver the following more concrete “products”.

9.1. Publications

At the end of the 5 year duration of this project, we expect to have published dozens of papers with the results of our research, both theoretical and empirical, in a variety of international, peer-refereed journals, as well as in proceedings of conferences, and as chapters in books. We plan in particular to submit some of our papers to the very top-ranking journals, such as *Nature* (impact factor about 30), *Science* (30), *Behavioral and Brain Sciences* (10) and *Psychological Review* (7).

Moreover, we plan to write at least two monographs:

- 1) a textbook for researchers and advanced students formally elaborating a conceptual framework for the modelling of distributed cognitive systems and their evolution. Following a similar structure as this proposal, it will start with the most simple element (objects, interactions, agents), and show how these can self-organize step by step to produce gradually more complex systems (groups, division of labor, distributed problem-solving, learning, coordination, etc.). The general principles will be illustrated with concrete examples, such as insect societies, organizations, group processes, socio-cultural evolution, or the coordination of software agents.
- 2) a practical handbook with exercises showing how to model distributed cognitive systems using our generic connectionist simulation environment (see below).

In addition, this project should produce at least three PhD dissertations, investigating different computational and empirical aspects of our general project.

9.2. Simulation environments

Many of the connectionist simulations will be conducted with the aid of a software program, called FIT, developed by **Van Overwalle**. As the program is extended with the results of our research, more advanced versions will be made freely available to the research community. Similarly, the KEBA multi-agent simulation environment [**Gershenson**, 2002] as it is extended with social self-organization and media sharing, will also be made available on the Internet. The initial versions of these and other software applications and demos developed by our group can already be downloaded from <http://pcp.vub.ac.be/ECCO/>

Eventually we will integrate these and other simulations in a general environment, combining the strengths of connectionist and multi-agent approaches, that can be used as a "virtual laboratory" for building models of self-organizing distributed cognitive systems, and experimenting with them. In this way, other researchers and students will be able not only to replicate our results, but to devise their own models and explore their properties in a flexible and user-friendly manner.

9.3. Empirical data

Like the software we develop, we also plan to make all the data gathered from our experiments and observations available via the web, so that other researchers can use them to re-analyse or to test their own hypotheses.

9.4. Workshops, conferences and lectures

Like in the past, we will continue to regularly organize international meetings on the subject of distributed cognition and its specific aspects, so that our work can be discussed with other researchers in the domain, and receive input from their results. The talks presented at the more important meetings will be published in the form of proceedings. We will also present our ideas in seminars and lectures for local colleagues and PhD students, and include the most important insights in the undergraduate courses we teach.

10. Project planning

The research project is scheduled to run for 5 years, from Jan. 1, 2006 to Dec. 31, 2010. The chart below summarizes the timeline for the different subprojects.

Year 1: 2006

In the first year, we will start with the two subprojects (8.4 and 8.5) that center around laboratory experiments, since these are most likely to be time-consuming, while running the greatest risk of failure, so that initial experiments may need to be redone or redesigned. For each of these two empirical projects we will need to employ a new research assistant (by means of a 4-year PhD scholarship) with a social science background, to set up and run the experiment and process the data.

In the meantime, the present members of the team will focus on the literature review, theoretical analysis and preliminary connectionist simulations, so as to put the conceptual framework on a firm foundation, while providing guidelines for the design of the experiments.

Year 2: 2007

In the second year, while the experiments and the theoretical and connectionist modelling are running, we will set up the more complex MAS simulations that form the core of subprojects 8.1.1, 8.1.2 and 8.2, building on the preliminary theoretical and empirical results. This will require the employment of another research assistant, with extensive computing experience, to program the simulations, run the different variations, collect and process the data. In this year, we also plan to organize a first project workshop with all team members and invited outside experts, to discuss the first results.

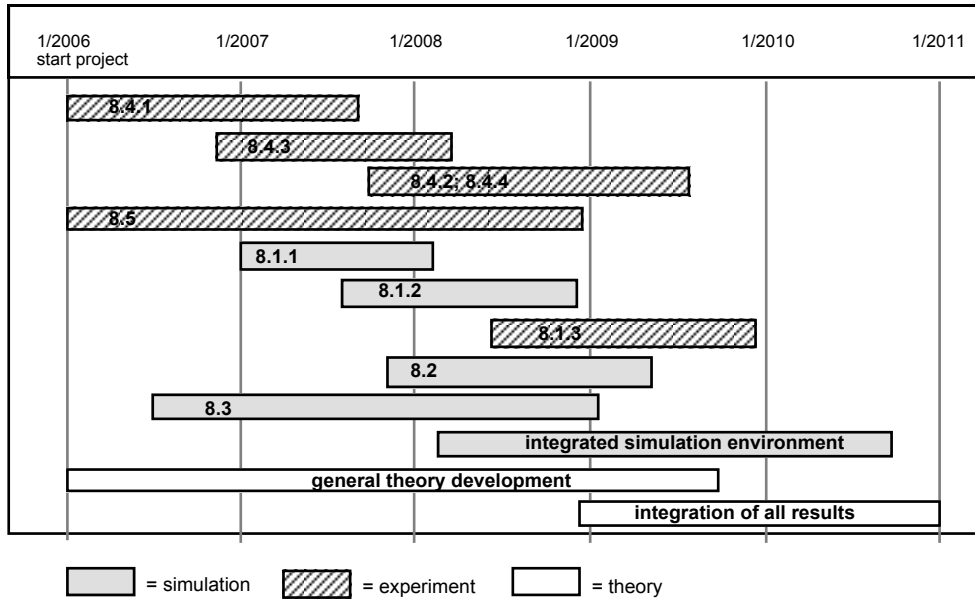


Figure: a timeline (Gantt chart) of the different subprojects or subtasks of the project with their estimated start and duration

Year 3: 2008

After two years of empirical data collection and connectionist simulation, and one year of MAS simulation, we will have sufficient material to start developing an integrated theoretical and simulation platform that combines MAS and connectionist principles (see subproject 8.3). This will require a fourth, more experienced researcher, at the PostDoc level. This researcher will keep close contact with the on-going experiments and agent simulations, to use their insights to build the integrated platform, and to suggest additional variations for testing. We should also have enough data from the simulation to try to replicate their results in a "business game" experiment (8.1.3). We will further run another project workshop to keep all people involved up-to-date about the advances and as yet unresolved issues.

Year 4: 2009

After three years of experiments, the two initial research assistants should have collected sufficient data to analyse and draw general conclusions so that they can defend their PhD dissertations on the subject by the end of the year. The simulations will continue to run different variations, while being extended with new insights and hypotheses coming from the experiments and theoretical investigations. A third international workshop is organized.

Year 5: 2010

After three years of agent simulations, the third research assistant too will have collected sufficient data to analyze and interpret in the form of a PhD dissertation. The PostDoc researcher will complete the development and data processing of the integrated platform. We conclude the project with a large, international conference on the broad subject of distributed cognition, with both invited and submitted papers from specialists around the world, during which the members of our team present all the major results of the project to the academic community.

Requested Funding

The following budget (all costs in Euro) provides an estimate of the funding we will need over the 5 years to run the project, split up into the different cost categories.

YEAR	2006	2007	2008	2009	2010	TOTAL
Purchase of books and journals	6000	4000	4000	3000	3000	20000
Travel and accomodation, to let team members participate in scientific conferences and visit research centers abroad	8000	8000	8000	8000	6000	38000
Organization of workshops and travel+ accommodation for visiting experts	4000	10000	10000	10000	20000	54000
Payment of participants in experiments (800 people x 7.5 euro/person)	6000	7000	7000	6000	2000	28000
Scientific Software licences (Statistics, experiment generator, development platforms...)	6000	5000	4000	3000	2000	20000
Various Scientific Material	1000	1000	1000	1000	1000	5000
computer equipment for PhD student 1	2500					2500
computer equipment for PhD student 2	2500					2500
computer equipment for PhD student 3		2500				2500
computer equipment for PostDoc 4			2500			2500
PhD scholarship 1	28979	29559	31737	32272		122547
PhD scholarship 2	28979	29559	31737	32272		122547
PhD scholarship 3		29559	31737	32272	32917	126485
PostDoc contract 4			61583	64296	70852	196731
TOTALS	93958	126177	193294	192112	137769	743310

Relevant publications of the research team

The following is a selection of the most important publications of the research team that are relevant for the present proposal.

- Bollen D.** (2004): Representation in situated models of cognition (ECCO working paper).
- Bollen J., Heylighen F.** (1996) Algorithms for the Self-organisation of Distributed, Multi-user Networks, in: *Cybernetics and Systems '96* R. Trappl (ed.), (Austrian Society for Cybernetics), p. 911-916.
- Bollen J.** (2001) *A Cognitive Model of Adaptive Web Design and Navigation - A Shared Knowledge Perspective*, Free University of Brussels, Faculty of Psychology, PhD Dissertation.
- Bollen J., Heylighen F.** (1998): A system to restructure hypertext networks into valid user models, *New Review of HyperMedia and Multimedia* 4, p. 189-213.
- Bollen, J., Heylighen F., Van Rooy D.** (1998): Improving Memetic Evolution in Hypertext and the WWW, in: *Proc. 16th Int. Congress on Cybernetics* (Association Internat. de Cybernétique, Namur), p. 449-454.
- Bollen, J.** (2000) Group User Models for Personalized Hyperlink Recommendations. In LNCS 1892 *International Conference on Adaptive Hypermedia and Adaptive Webbased Systems* (AH2000), pages 39-50, Trento, August . Springer Verlag.
- Chielens K., Heylighen F.** (2004): Operationalization of Meme Selection Criteria: Methodologies to Empirically Test Memetic Prediction, in: *Proceedings of the Joint Symposium on Socially Inspired Computing, AISB 2005 Convention*, p. 14-20.
- Chielens, K.** (2003) *The Viral Aspects of Language: A Quantitative Research of Memetic Selection Criteria*. Unpublished Masters Thesis VUB.
- De Jaegher L.** (2004). Management of Uncertainty and the Balance between Precaution and Innovation: Towards new strategies for a sustainable risk management, *Bioscience Law Review*, Lawtext Publishing.
- Gershenson C.** (2001). *Artificial Societies of Intelligent Agents*. Unpublished BEng Thesis. Fundacion Arturo Rosenblueth, Mexico.
- Gershenson C.** (2002a). Philosophical Ideas on the Simulation of Social Behaviour. *Journal of Artificial Societies and Social Simulation* vol. 5, no. 3.
- Gershenson C.** (2002b). Behaviour-based Knowledge Systems: An Epigenetic Path from Behaviour to Knowledge. *Proceedings of the 2nd Workshop on Epigenetic Robotics*. Edinburgh.
- Gershenson C.** (2003). Comparing Different Cognitive Paradigms with a Virtual Laboratory. *IJCAI-03: Proceedings of the Eighteenth International Joint Conference on Artificial Intelligence*, pp. 1635-6. Morgan Kaufmann.
- Gershenson C.** (2004). Cognitive Paradigms: Which One is the Best? *Cognitive Systems Research*, 5(2):135-156,.
- Gershenson C.** (2005) Self-organizing Traffic Lights. (ECCO working paper 2005-02)
- Gershenson C., Heylighen F.** (2003). When Can we Call a System Self-organizing?, In Banzhaf, W, T. Christaller, P. Dittrich, J. T. Kim and J. Ziegler (eds.), *Advances in Artificial Life, 7th European Conference, ECAL 2003*, (Springer, LNAI 2801.), p. 606-614.
- Gershenson C., Heylighen F.** (2004a). How can we think the complex? in: Richardson, Kurt (ed.) *Managing the Complex Vol. 1: Philosophy, Theory and Application*. [in press]
- Gershenson C., Heylighen F.** (2004b): Protocol Requirements for Self-organizing Artifacts: Towards an Ambient Intelligence, in: *Proc. Int. Conf. on Complex Systems* (New England Institute of Complex Systems)
- Gershenson C., M. A. Porter, A. Probst, M. Marko and A. Das.** (2002) A Study on the Relevance of Information in Discriminative and Non-Discriminative Media. *InterJournal of Complex Systems* , 533.
- Gershenson C., P. P. González and J. Negrete.** (2000a) Action Selection Properties in a Software Simulated Agent, in Cairó et. al. (Eds.) *MICAI 2000: Advances in*

- Artificial Intelligence*. Lecture Notes in Artificial Intelligence 1793, pp. 634-648. Springer-Verlag.
- Gershenson C.**, P. P. González and J. Negrete. (2000b) Thinking Adaptive: Towards a Behaviours Virtual Laboratory. In Meyer et. al. (eds.) *Simulation of Adaptive Behavior 2000 Proceedings Supplement*. Paris, France. ISAB press.
- Heylighen F.** (1989): Causality as Distinction Conservation: a theory of predictability, reversibility and time order, *Cybernetics and Systems* 20, p. 361-384.
- Heylighen F.** (1989): Self-Organization, Emergence and the Architecture of Complexity, in: *Proc. 1st European Conference on System Science*, (AFCET, Paris), p. 23-32.
- Heylighen F.** (1990a): Autonomy and Cognition as the Maintenance and Processing of Distinctions, in: *Self-Steering and Cognition in Complex Systems*, **Heylighen F.**, Rosseel E., Demeyere F. (ed.), (Gordon and Breach, New York), p. 89-106.
- Heylighen F.** (1990b): *Representation and Change. A Metarepresentational Framework for the Foundations of Physical and Cognitive Science*, (Communication and Cognition, Gent), 200 p.
- Heylighen F.** (1990c): A New Transdisciplinary Paradigm for the Study of Complex Systems?, in: *Self-Steering and Cognition in Complex Systems*, **Heylighen F.**, Rosseel E., Demeyere F. (ed.), (Gordon and Breach, New York), p. 1-16.
- Heylighen F.** (1991): Cognitive Levels of Evolution: pre-rational to meta-rational, in: *The Cybernetics of Complex Systems - Self-organization, Evolution and Social Change*, F. Geyer (ed.), (Intersystems, Salinas, California), p. 75-91.
- Heylighen F.** (1991): Design of a Hypermedia Interface Translating between Associative and Formal Representations, *International Journal of Man-Machine Studies* 35, p. 491-515.
- Heylighen F.** (1991): Modelling Emergence, *World Futures: the Journal of General Evolution* 31 (Special Issue on Emergence, edited by G. Kampis), p. 89-104.
- Heylighen F.** (1992) : ‘Selfish’ Memes and the Evolution of Cooperation, *Journal of Ideas* , Vol. 2, #4, pp 77-84.
- Heylighen F.** (1992) : Evolution, Selfishness and Cooperation, *Journal of Ideas*, Vol 2, # 4, pp 70-76.
- Heylighen F.** (1992): A Cognitive-Systemic Reconstruction of Maslow’s Theory of Self-Actualization, *Behavioral Science* 37, p. 39-58.
- Heylighen F.** (1992): Principles of Systems and Cybernetics: an evolutionary perspective, in: *Cybernetics and Systems ‘92*, R. Trappl (ed.), (World Science, Singapore), p. 3-10.
- Heylighen F.** (1992): Non-Rational Cognitive Processes as Changes of Distinctions, in: *New Perspectives on Cybernetics. Self-Organization, Autonomy and Connectionism*, G. Van de Vijver (ed.), (Synthese Library v. 220, Kluwer Academic, Dordrecht), p. 77-94.
- Heylighen F.** (1993): Selection Criteria for the Evolution of Knowledge, in: *Proc. 13th Int. Congress on Cybernetics* (Association Internat. de Cybernétique, Namur), p. 524-528.
- Heylighen F.** (1994) Fitness as Default: the evolutionary basis for cognitive complexity reduction, in: *Cybernetics and Systems ‘94*, R. Trappl (ed.), (World Science, Singapore), p.1595-1602.
- Heylighen F.** (1995): (Meta)systems as constraints on variation, *World Futures: the Journal of General Evolution* .45, p. 59-85.
- Heylighen F.** (1997): Objective, subjective and intersubjective selectors of knowledge, *Evolution and Cognition* 3:1, p. 63-67.
- Heylighen F.** (1997): The Economy as a Distributed, Learning Control System, *Communication and Cognition- AI* 13, nos. 2-3, p. 207-224.
- Heylighen F.** (1998): What makes a meme successful? Selection criteria for cultural evolution, in: *Proc. 16th Int. Congress on Cybernetics* (Association Internat. de Cybernétique, Namur), p. 423-418.
- Heylighen F.** (1999): Collective Intelligence and its Implementation on the Web: algorithms to develop a collective mental map, *Computational and Mathematical Organization Theory* 5(3), p. 253-280.

- Heylighen F.** (1999b): The Growth of Structural and Functional Complexity during Evolution, in: F. **Heylighen**, J. **Bollen** and A. Riegler (eds.) *The Evolution of Complexity* (Kluwer Academic, Dordrecht), p. 17-44.
- Heylighen F.** (2000): Foundations and Methodology for an Evolutionary World View: a review of the Principia Cybernetica Project, *Foundations of Science*, 5, p. 457-490.
- Heylighen F.** (2001a): Bootstrapping knowledge representations: from entailment meshes via semantic nets to learning webs, *Kybernetes* 30 (5/6), p. 691-722.
- Heylighen F.** (2001b): Mining Associative Meanings from the Web: from word disambiguation to the global brain, in: *Proceedings of the International Colloquium: Trends in Special Language and Language Technology*, R. Temmerman and M. Lutjeharms (eds.) (Standaard Editions, Antwerpen), p. 15-44.
- Heylighen F.** (2002): The Science of Self-organization and Adaptivity, in: Knowledge Management, Organizational Intelligence and Learning and Complexity, in: *The Encyclopedia of Life Support Systems*, (Eolss Publishers, Oxford).
- Heylighen F.** (2004): Mediator Evolution: a general scenario for the origin of dynamical hierarchies, *Artificial Life* [submitted]
- Heylighen F.** (2004): The Global Superorganism: an evolutionary-cybernetic model of the emerging network society, *Journal of Collective Intelligence*[submitted]
- Heylighen F., Bollen J.** (1996) The World-Wide Web as a Super-Brain: from metaphor to model, in: *Cybernetics and Systems '96* R. Trappl (ed.), (Austrian Society for Cybernetics),p. 917-922.
- Heylighen F., Bollen J.** (2002): Hebbian Algorithms for a Digital Library Recommendation System, in *Proceedings 2002 International Conference on Parallel Processing Workshops* (IEEE Computer Society Press)
- Heylighen F., Bollen J., Riegler A.** (ed.) (1999): *The Evolution of Complexity* (Kluwer Academic, Dordrecht).
- Heylighen F., Campbell D.T.** (1995): Selection of Organization at the Social Level: obstacles and facilitators of metasystem transitions, *World Futures: the Journal of General Evolution* 45, p. 181-212.
- Heylighen F., Dewaele J-M.** (2002): Variation in the contextuality of language: an empirical measure, *Foundations of Science* 6, p. 293-340
- Heylighen F., Gershenson C.** (2003): The Meaning of Self-organization in Computing, *IEEE Intelligent Systems* 18:4, p. 72-75.
- Heylighen F., Heath M.** (eds.) (2005): From Intelligent Networks to the Global Brain, special issue of *Technological Forecasting and Social Change* (in press)
- Heylighen A., Heylighen F., Bollen J., Casaer M.** (2005): A distributed model for tacit design knowledge exchange, *Proceedings of Social Intelligence Design 2005*, R. Fruchter (ed.).
- Heylighen F., Heath M., F. Van Overwalle** (2004): The Emergence of Distributed Cognition: a conceptual framework, *Proceedings of Collective Intentionality IV*, Siena (Italy).
- Heylighen F., Joslyn C., Turchin V.** (eds.) (1993-2005): Principia Cybernetica Web (<http://pespmc1.vub.ac.be/>),
- Heylighen F., Joslyn C.** (1993): Electronic Networking for Philosophical Development in the Principia Cybernetica Project, *Informatica* 17, No. 3, p. 285-293.
- Heylighen F., Joslyn C.** (1995): Systems Theory, in: *The Cambridge Dictionary of Philosophy*, R. Audi (ed.) (Cambridge University Press, Cambridge), p.784-785.
- Heylighen F., Joslyn C.** (2001): Cybernetics and Second Order Cybernetics, in: R.A. Meyers (ed.), *Encyclopedia of Physical Science and Technology* (3rd ed.), Vol. 4 , (Academic Press, New York), p. 155-170.
- Heylighen F., Rosseel E., Demeyere F.** (eds.) (1990): *Self-Steering and Cognition in Complex Systems. Toward a New Cybernetics*, (Gordon and Breach Science Publishers, New York), 440 p.
- Jordens, K., Van Overwalle, F.** (2004). Connectionist Modeling of Attitudes and Cognitive Dissonance. In G. Haddock, G. Maio (Eds.) *Contemporary perspectives on the psychology of attitudes*. London: Psychology Press.

- Jordens, K., **Van Overwalle, F.** (submitted) *Cognitive dissonance and affect: An empirical test of a connectionist account.*
- Martens B.** (1998): The relationship between knowledge and economic growth: an economic-cognitive approach *Proc. 23rd Flemish Economic Congress*, Leuven.
- Martens B.** (1999): The introduction of complexity concepts in economics: towards a new paradigm, in: F. **Heylighen**, J. **Bollen** and A. Riegler (eds.) *The Evolution of Complexity* (Kluwer Academic, Dordrecht),
- Martens B.** (1999): Towards a Generalised Coase Theorem: a theory of the emergence of social and institutional structures under imperfect information, in Barnett et al, (eds.): *Commerce, Complexity and Evolution*, Cambridge University Press.
- Martens B.** (2005): *The cognitive mechanics of economic development and institutional change*, (Cambridge University Press). (in press)
- Martens B.**, P. Murrell, P. Seabright and U. Mummert (2002), *The institutional economics of foreign aid*, Cambridge University Press.
- Rocha L. M., J. **Bollen** (2000). Biologically motivated distributed designs for adaptive knowledge management. In I.Cohen and L. Segel, editors, *Design Principles for the Immune System and other Distributed Autonomous Systems*, Oxford University Press. pp. 305-334.
- Rodriguez, M.** (2004), Advances Towards a General-Purpose Human-Collective Problem-Solving Engine, *Proc. International Conference on Systems, Man and Cybernetics*, IEEE SMC.
- Rodriguez, M.** (2005), The Convergence of Digital Library Technology and the Peer-Review Process. (ECCO working paper 2005-04, submitted to *Journal of Information Science*)
- Rodriguez, M.**, Steinbock, D. (2004), A Social Network for Societal-Scale Decision-Making Systems, *Proc. North American Association for Computational Social and Organizational Science Conference.*
- Timmermans, B.**, Cleeremans, A. (2000). Rules versus statistics in biconditional grammar learning. *Proceedings of the 22nd Annual Meeting of the Cognitive Science Society*, 947-952. NJ: Erlbaum
- Timmermans, B.**, **Van Overwalle F.** (submitted) Spontaneous circumstantial attributions.
- Van Overwalle F.**, Siebler, F. (2005). A Connectionist Model of Attitude Formation and Change. *Personality and Social Psychology Review*, in press.
- Van Overwalle F.**, **Timmermans, B.** (2005) Discounting and the Role of the Relation between Causes. *European Journal of Social Psychology*, in press.
- Van Overwalle F.** (1989). Structure of freshmen's causal attributions for exam performance. *Journal of Educational Psychology*, 81, 400-407.
- Van Overwalle F.** (1997a) Dispositional attributions require the joint methods of difference and agreement. *Personality and Social Psychology Bulletin*, 23, 974-980.
- Van Overwalle F.** (1997b) A test of the Joint model of causal attribution. *European Journal of Social Psychology*, 27, 221-236.
- Van Overwalle F.** (1998) Causal explanation as constraint satisfaction : A critique and a feedforward connectionist alternative. *Journal of Personality and Social Psychology*, 74, 312-328.
- Van Overwalle F.** (2003) Acquisition of dispositional attributions: Effects of sample size and covariation. *European Journal of Social Psychology*, 33, 515—533.
- Van Overwalle F.** (2004). Multiple Person Inferences: A View of a Connectionist Integration. In H. Bowman, C. Labiouse (Eds.), *Proceedings of the Eighth Neural Computation and Psychology Workshop* (Progress in Neural Processing). London, UK: World Scientific
- Van Overwalle F.** (under revision) *Discounting and augmentation of dispositional and causal attributions.*
- Van Overwalle F.**, Labiouse, C. (2004) A recurrent connectionist model of person impression formation. *Personality and Social Psychology Review*, 8, 28-61.

- Van Overwalle F., Drenth, T., Marsman, G.** (1999). Spontaneous trait inferences : Are they linked to the actor or to the action ? *Personality and Social Psychology Bulletin*, 25, 450-462.
- Van Overwalle F., Heylighen, F.** (1991). Invariantie-kenmerken bij antecedente condities en attributionele dimensies : Waarnemen van oorzaken, verwachtingen en emoties. [Invariance features in antecedent conditions and attributional dimensions: Perceiving causes, expectations and emotions] In J. van der Pligt, W. van der Kloot, A. van Knippenberg and M. Poppe (Eds.) *Fundamentele sociale psychologie: Deel 5* (pp. 44-60). Tilburg : Tilburg University Press.
- Van Overwalle F., Heylighen, F.** (1995) Relating covariation information to causal dimensions through principles of contrast and invariance. *European Journal of Social Psychology*, 25, 435-455.
- Van Overwalle F., Heylighen, F., Casaer, S., Daniëls, M.** (1992). Preattributional and attributional determinants of emotions and expectations. *European Journal of Social Psychology*, 22, 313-329.
- Van Overwalle, F., Heylighen, F., Heath, M.** (2005) *Trust in Communication between Individuals: A Connectionist Approach*. Proceedings of the Cognitive Science 2005 Workshop: Toward Social Mechanisms of Android Science.
- Van Overwalle, F., Jordens, K.** (2002). An adaptive connectionist model of cognitive dissonance. *Personality and Social Psychology Review*, 3, 204—231.
- Van Overwalle, F., Labiouse, C.** (2004) A recurrent connectionist model of person impression formation. *Personality and Social Psychology Review*, 8, 28—61.
- Van Overwalle, F., Mervielde, I., De Schuyter,** (1995). Structural modeling of the relationships between attributions, emotions and behavior of college freshmen. *Cognition and Emotion*, 9, 59-85.
- Van Overwalle, F., Siebler, F.** (submitted). A Connectionist Model of Attitude Formation and Change.
- Van Overwalle, F., Timmermans, B.** (2001). Learning about an Absent Cause: Discounting and Augmentation of Positively and Independently Related Causes. French, R.M., Sougné, J.P. (Eds.) *Connectionist Models of Learning, Development and Evolution: Proceedings of the Sixth Neural Computation and Psychology Workshop, Liege, Belgium, 16-18 September 2000*. Springer Verlag.
- Van Overwalle, F., Timmermans, B.** (under revision) Discounting and augmentation in attribution: The role of the relationship between causes.
- Van Overwalle, F., Van Rooy, D.** (2001a). How one cause discounts or augments another: A connectionist account of causal competition. *Personality and Social Psychology Bulletin*, 27, 1613—1626.
- Van Overwalle, F., Van Rooy, D.** (2001b). When more observations are better than less : A connectionist account of the acquisition of causal strength. *European Journal of Social Psychology*, 31, 155-175.
- Van Overwalle, F., Van Rooy, D.** (1998) A Connectionist Approach to Causal Attribution. In S. J. Read, L. C. Miller (Eds.) *Connectionist and PDP models of Social Reasoning and Social Behavior* (pp. 143—171). Lawrence Erlbaum.
- Van Rooy, D.** (2000): *A connectionist model of illusory correlation*. (PhD Thesis, Vrije Universiteit Brussel).
- Van Rooy, D., Van Overwalle, F.** (submitted) Illusory correlation, sample size and memory: A connectionist approach.
- Van Rooy, D., Van Overwalle, F., Vanhooissen, T., Labiouse, C., French, R.** (2003). A recurrent connectionist model of group biases. *Psychological Review*, 110, 536-563.

Bibliography (publications by others)

- Ahuja MK, KM Carley (1999): Network structure in virtual organizations, *Organization Science*, 10 n.6, p.741-757
- Ashby, W. R. (1962). Principles of the Self-organizing System. In von Foerster, H. and G. W. Zopf, Jr. (Eds.), *Principles of Self-organization*. Pergamon Press, pp. 255-278.
- Aunger R. (ed.) (2001): *Darwinizing Culture: The Status of Memetics As a Science* (Oxford University Press)
- Axelrod, R. M., *The Evolution of Cooperation*, Basic Books New York (1984).
- Bavelas A. (1950): Communication patterns in task-oriented groups, *Journal of the Acoustical Society of America*, 22, 723-730
- Belpaeme T. (2001) Reaching coherent color categories through communication. In Kröse, B. et al. (eds.), *Proc. 13th Belgium-Netherlands Conference on AI*, Amsterdam, p. 41-48.
- Berger P. L., T. Luckmann: (1967) *The Social Construction of Reality: A Treatise in the Sociology of Knowledge*, Anchor.
- Berners-Lee T., J. Hendler & O. Lassila (2001): The Semantic Web, *Scientific American*, 282(5),
- Bonabeau E., Dorigo M. and Theraulaz G. (1999) *Swarm intelligence: From natural to artificial systems*. Oxford University Press.
- Brauer, M., Judd, C. M., & Jacquelin (2001). The communication of social stereotypes: The effects of group discussion and information distribution on stereotypic appraisals. *Journal of Personality and Social Psychology*, 81, 463—475.
- Cantwell Smith, B. (1996): *On the origin of objects* (MIT Press)
- Castelfranchi C. & R. Falcone (2000). Social trust: A cognitive approach. In C. Castelfranchi and Yao-Hua Tan, editors, *Trust and Deception in Virtual Societies*, pages 55–90. Kluwer Academic Publishers, .
- Clark A. and Chalmers D. (1998):, The Extended Mind, *Analysis* 58, p. 7-19.
- Clark, A. (1997). *Being There: putting brain, body, and world together again*, Cambridge, Mass., MIT Press.
- Corning, Peter. (1995), Synergy and Self-organization in the Evolution of Complex Systems. *Systems Research* 12(2): 89-121.
- Crowston, K. (2003). A taxonomy of organizational dependencies and coordination mechanisms. In Malone, T. W., Crowston, K. and Herman, G. (Eds.) *Tools for Organizing Business Knowledge: The MIT Process Handbook*. Cambridge, MA: MIT Press.
- Crutchfield J. (1998). Dynamical embodiments of computation in cognitive processes, *Behavioral and Brain Sciences*, 21, p. 635.
- Crutchfield J., Shalizi C., Tumer K & Wolpert D. (eds.) (2002): *Collective Cognition Workshop Proceedings: Mathematical Foundations of Distributed Intelligence* (<http://www.santafe.edu/~dynlearn/colcog/>, to be published in the Santa Fe Institute Studies in the Sciences of Complexity, Oxford University Press;)
- Dastani, M., J. Hulstijn, & L. Van der Torre (2001), Negotiation protocols and dialogue games, *International Conference on Autonomous Agents, ACM* , 180 – 181.
- Ebbesen, E. B. & Bowers, R. J. (1974). Proportion of risky to conservative arguments in a group discussion and choice shift. *Journal of Personality and Social Psychology*, 29, 316—327.
- Fiedler, K. (1991). The tricky nature of skewed frequency tables: An Information loss account of distinctiveness -based illusory correlations. *Journal of Personality and Social Psychology*, 60, 24-36.
- Fiske, S. F. (2005). *Social beings: A core motives approach to social psychology*. Hoboken, JN: Wiley.
- Foltz P.W. (1996) Latent Semantic Analysis for text-based research, *Behavior Research Methods, Instruments, & Computers*, 28, 197-202.
- Gaines B.R. (1994), The Collective Stance in Modeling Expertise in Individuals and Organizations, *Int. J. Expert Systems* 71, 22-51.

- Garrod, S. & Doherty, G. (1994) Conversation, co-ordination and Convention: An empirical investigation of how groups establish linguistic conventions. *Cognition*, 53,181-215.
- Garrod, S. (1998) How groups co-ordinate their concepts and terminology: Implications for Medical Informatics. *Methods of Information in Medicine*, 37, 471-477.
- Guetzkow, H. & Simon, H. A. (1955). The impact of certain communication nets upon organization and performance in task oriented groups. *Management Science*, 1, 233-50.
- Heath C., Bell C. & Sternberg E. 2001. Emotional Selection in Memes: The Case of Urban Legends. *Journal of Personality and Social Psychology* 81(6):1028-1041.
- Hollan, J., Hutchins, E., & Kirsch, D. (2001) "Distributed Cognition: Toward a New Foundation for Human-Computer Interaction Research." In J. M. Carroll (Ed.), *Human-Computer Interaction in the New Millennium*, ACM Press, New York, pp. 75-94.
- Hutchins E (1995): *Cognition in the Wild* (MIT Press).
- Hutchins, E. & B. Hazelhurst (1995). How to invent a lexicon: the development of shared symbols in interaction. In N. Gilbert and R. Conte (Eds.), *Artificial Societies*. UCL Press
- Isenberg, D. J. (1986). Group polarization: A critical review and meta-analysis. *Journal of Personality and Social Psychology*, 50, 1141—1151.
- ISTAG (2003): *Ambient Intelligence: from vision to reality* (report to the European Commission, available at <http://www.cordis.lu/ist/istag.htm>)
- Janis, I. L. (1972) *Victims of groupthink*. (Boston: Houghton Mifflin).
- King-Casas, B., Tomlin, D., Anen, C., Camerer, C. F., Quartz, S. R. & Montague, R. (2005). Getting to Know You: Reputation and Trust in a Two-Person Economic Exchange. *Science*, 308, 78—83.
- Kirsch, D. & Maglio, P. (1994) On distinguishing epistemic from pragmatic action. *Cognitive Science* 18: 513-549
- Kirsh, D. (1996) Adapting the Environment Instead of Oneself. *Adaptive Behavior*, Vol 4, No. 3/4, 415-452.
- Klein, O. Jacobs, A., Gemoets, S. Licata, L. & Lambert, S. (2003). Hidden profiles and the consensualization of social stereotypes: how information distribution affects stereotype content and sharedness. *European Journal of Social Psychology*, 33, 755—777.
- Krauss, R.M. & Weinheimer, S. (1964). Changes in reference phrases as a function of frequency of usage in social interaction: A preliminary study. *Psychonomic Science*, 1, 113—114.
- Larson, Jr, J. R., Christensen, C., Abbott, A. S. & Franz, T. M. (1996). Diagnosing groups: Charting the flow of information in medical decision-making teams. *Journal of Personality and Social Psychology*, 71, 315—330.
- Larson, Jr., J. R., Foster-Fishman, P. G. & Franz, T. M. (1998). Leadership style and the discussion of shared and unshared information in decision-making groups. *Personality and Social Psychology Bulletin*, 24, 482—495.
- Leavitt, H. J. (1951). Some effects of certain communication patterns on group performance. *Journal of Abnormal and Social Psychology*, 46, 38—50.
- Lévy P. (1997): *Collective Intelligence*, Plenum.
- Lyons, A. & Kashima, Y. (2003) How Are Stereotypes Maintained Through Communication? The Influence of Stereotype Sharedness. *Journal of Personality and Social Psychology*, 85, 989-1005.
- Mackenzie, K. D. (1976). *A theory of group structure*. New York: Gordon & Breach.
- Mackie, D. & Cooper, J. (1984) Attitude polarization: Effects of group membership. *Journal of Personality and Social Psychology*, 46 (3), 575—585.
- McLeod, P., Plunkett, K. & Rolls, E. T. (1998). *Introduction to connectionist modeling of cognitive processes*. Oxford, UK: Oxford University Press.
- Neisser U. (1976), *Cognition and Reality: Principles and Implications of Cognitive Psychology*. WH Freeman,

- Riolo, R., M. D. Cohen, and R. M. Axelrod (2001), Evolution of cooperation without reciprocity, *Nature* 414, 441–443.
- Rosch, E. (1981). Categorization of natural objects. *Annual Review of Psychology*, 32, 89–115.
- Rumelhart D.E. & J.L. McClelland (editors) (1986): *Parallel Distributed Processing: Explorations in the Microstructure of Cognition*, volume 1. MIT Press.
- Schober, M. F. & Clark, H. H. (1989). Understanding by addressees and overhearers. *Cognitive Psychology*, 21, 211–232.
- Searle, J. (1995): *The Construction of Social Reality*, Free Press
- Senge P. (1990) *The Fifth Discipline: the Art and Practice of Learning Organizations*, Doubleday.
- Shaw, M. E. (1964). Communication networks. In L. Berkowitz (Ed.) *Advances in Experimental Social Psychology*, 1, 111-147. New York: Academic Press.
- Shum S.B., Vi. Uren, G. Li, Jo. Domingue, E. Motta (2003): Visualizing Internetworked Argumentation, In: *Visualizing Argumentation: Software Tools for Collaborative and Educational Sense-Making*. Paul A. Kirschner, Simon J. Buckingham Shum and Chad S. Carr (Eds), . Springer-Verlag: London
- Staab S. & Studer R., (eds.) (2003), *Handbook on Ontologies in Information Systems*, Springer Verlag.
- Stasser, G. (1999). The uncertain role of unshared information in collective choice. In L. L. Thompson, J. M. Levine & D. M. Messick (Eds.) *Shared Cognition in Organizations: The management of Knowledge* (pp 49—69). Mahwah, NJ: Erlbaum.
- Steels L. & Brooks R. (eds.) (1995): *The Artificial Life Route to Artificial Intelligence: Building Embodied Situated Agents* (Erlbaum).
- Steels L. (1998): Synthesising the origins of language and meaning using co-evolution, self-organisation and level formation, in Hurford et al. (eds): *Approaches to the evolution of language* (Cambridge University Press), p. 384-404.
- Surowiecki, J. (2004). The wisdom of crowds: Why the many are smarter than the few and how collective wisdom shapes business, economics, societies, and nations. New York: Doubleday.
- Susi, T. & Ziemke, T. (2001). Social Cognition, Artefacts, and Stigmergy: A Comparative Analysis of Theoretical Frameworks for the Understanding of Artefact-mediated Collaborative Activity. *Cognitive Systems Research*, 2(4), 273-290.
- von Foerster, H., (1960). On self-organising systems and their environments, in: *Self-Organising Systems*, M.C. Yovits and S. Cameron (eds.), Pergamon Press, London, pp. 30-50.
- Weiss G. (1999): *Multiagent systems: a modern approach to distributed artificial intelligence*, (Cambridge, Mass. : MIT Press).
- Wittenbaum, G. M. & Bowman, J. M. (2003). A social validation explanation for mutual enhancement. *Journal of Experimental Social Psychology*, 40, 169—184.
- Wright, R.(2000): *Non-Zero. The Logic of Human Destiny* (Pantheon Books)

5 suggesties van externe experts voor de screening van het projectvoorstel

Dr. Cliff Joslyn:
Distributed Knowledge Systems and Modelling team,
MS B265, Los Alamos National Laboratory
Los Alamos, NM 87545 USA
tel + 1- (505) 667-9096
joslyn@lanl.gov
<http://www.c3.lanl.gov/~joslyn>

Dr . Ben Goertzel
Novamente, inc.
14409 Oakvale Street
Rockville, MD 20853, USA
tel. : +1- 505/301-8936
ben@goertzel.org
<http://www.goertzel.org/ben/newResume.htm>

Dr. Bruce Edmonds
Centre for Policy Modelling
Manchester Metropolitan University
Aytoun Building, Aytoun Street, Manchester M1 3GH, UK.
Tel. +161 247 6479 Fax. +161 247 6802
bruce@cfpm.org
<http://bruce.edmonds.name/>

Prof. Stuart Umpleby,
Research Program in Social and Organizational Learning
The George Washington University
2101 F Street NW, Suite 201, Washington, DC 20052 USA
Fax: +1- 202-994-3081
umpleby@gwu.edu
<http://www.gwu.edu/~umpleby/bio.html>

Dr. Yoshi Kashima
Department of Psychology, School of Behavioural Science
12th Floor, Redmond Barry Building
The University of Melbourne, Victoria 3010, Australia
Telephone: (+61 3) 8344 6312
y.kashima@psych.unimelb.edu.au
<http://www.psych.unimelb.edu.au/staff/kashima.html>

experten die niet voor de screening van het ingediende projectvoorstel mogen worden gecontacteerd:

Porf. Luc Steels (AI-lab, VUB)