Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 35 (2014) 1043 – 1052

Procedia Computer Science

18th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems - KES2014

A review of cognitive decision-making within future mission systems

Jeffrey W. Tweedale[a,b,*]

[a]DSTO, PO Box 1500, Edinburgh, South Australia, 5111, Australia
[b]KES, ITEE, University of South Australia, Mawson Lakes, 5095, Australia

Abstract

This paper provides an outline of historical attempts to achieve human-like decision-making within machines. It concludes with a proposed conceptual approach of how researchers might pursue cognitive mission systems designs in the future. A number of potential success stories need to be explored in order to revise existing techniques and identify which techniques could be componentised for use in this future design. Existing cognitive systems have evolved over time, using; LISt Processing (LISP), PROLOG and Object Oriented Programming (OOP) languages. These were used to represent information using lists, scripts, frames, schemas, production rules, procedural, semantic and declarative processes. As Computational Intelligence (CI) techniques evolved, a number of frameworks emerged; such as Recognition-Primed Decision (RPD), Procedural Reasoning System (PRS), Collaborative Agent for Simulating Teamwork (CAST), Adaptive Character of Thought–Rational (ACT-R), distributed Multi-Agent Reasoning System (dMars), State, Operator And Result (SOAR) and Java Agent Compiler and Kernel (JACK). Many of these failed to gain traction because the problem-space has become more complex and existing heuristic code quickly becomes unwieldy with no guaranteed solution. Although currently heuristic systems relieve humans of routine activities, they are not able to independently reproduce intuition, insight or cognitive learning. Researchers have repetitively attempted to enhance the level of decision-making capabilities, but few have achieved success without augmented human support. Emerging frameworks continue to re-use a number of recurring themes to solve constrained problems, although most techniques cannot transform information into knowledge or wisdom. This paper highlights a number of the more successful concepts that could be used to progressively derive components to form a working cognitive decision-making model within a future mission system.

Peer-review under responsibility of KES International.

Keywords: Agents; Artificial Intelligence; Cognitive Architecture; Computational Intelligence; Decision-Making; Machine Intelligence; Multi-Agent Systems.

1. Introduction

Dreyfus cites that Artificial Intelligence (AI) began as a *continuum hypothesis* aimed at formalizing common sense understanding within intelligent machines [1]. In 1957 Newell predicted that a computer would be a world

*J.W. Tweedale. Tel.: +618-7389-6457; fax: +618-7389-5507.

1877-0509
Peer-review under responsibility of KES International.
doi:10.1016/j.procs.2014.08.191

champion chess player within ten years [2]. In 1965, Simons heralded that "Within twenty years, machines will be capable of doing any work that a human can do" [3]. In 1979 McCorduck introduced the concepts associated with how machines can *Think* using AI techniques [4]. She inferred that *calculative rationality* can improve society, although history reveals there has been limited success. Similarly, Dreyfus interjected, that "AI must wait for a computer with an entirely different design. One that reflects a prototype of the little understood human brain" although in 1986 he added that computers will influence society and he considered as a disruptive technology that would stimulate significant change within many organisations [1].

More recently, computer scientists aspire to amplify human reasoning within a *virtual mind*, ultimately emulating cognitive capabilities within silicon systems. Unfortunately genuine *know-how*, *wisdom* and *good judgement* may be sacrificed in the process, however explicit and logical automation will eventually emerge. Dreyfus indicates that human *intuition* is *real* and concludes that it usurps *declarative or rule-based decision-making* [1]. For example, in 1948 he cites the process of chicken sexing [5] as a turning point in concepts associated with learning systems. This resulted in Benner documenting his five stages of cognitive learning. These include: novice, advanced beginner, competent, proficient and expert [1]. Here, specific events escalate, starting from *context free*, *situation*, *competence*, *proficiency* and *expertise* [6]. Similarly, the Set goals, Think, Act, Review and Supply improvement (Stars) approach recently evolved to guide researchers when acquiring knowledge [7].

These processes transitioned into machine learning systems. The first significant examples used the *Saphira* software architecture – 1997. This was a layered control operating system that the replaced the original Procedural Reasoning System (PRS) controller used in the Stanford Research Institute (SRI) robot called *Flakey* introduced in 1992. This robot was a reactive control system based on a natural language interface (voice synthesis and recognition), 12 radially spaced sonar sensors and a stereo vision (dual cameras mounted on a pan/tilt head) [8]. This software constructed a synthetic representation of its local environment using low-level occupancy grids [9]. This system allows external control features that can also be stored (as *artefacts*) to assist with navigation and real-world orientation. Regardless of the platform, its underlying theories of learning and cognition will continue to challenge researchers across multiple domains.

Over time, both 'Production systems' and the Beliefs, Desires and Intent (BDI) frameworks have become popular. They both produced a long pedigree of commercial-strength solutions. This longevity indicates that the founding concepts are both sound and extensible. This is clearly illustrated in the progression of BDI implementations from PRS – 1986 [10] to dMARS – 1997 [11] to JACK – 1997 [12] and eventually JACK Teams – 2004 [13]. Other success stories include Jennings' GRATE – 1995 [14], Tambes' STEAM – 1997 [15][1] and Tidhars' Battle Model – 1999 [16]. New team based cognitive concepts may gain favour. Some example include: norms, obligation and commitment. Ultimately each of these concepts must be capable of scaling to solve real-world problems. They should also be capable of performing higher-level cognitive decision-making. Hence this paper attempts to discuss a number of successful mechanisms that could be integrated to achieve enhanced performance and focus on achieving increasing levels of cognitive decision-making.

Section 2 provides background information about the experts and concepts. Section 3 introduces concepts associated with PRS and Recognition-Primed Collaborative Agent for Simulating Teamwork (R-CAST) – 2001, while Section 4 discusses a basic schematic of the proposed cognitive mission system. Finally, Section 5 highlights this author's conclusion and possible future activities.

2. Background

Dreyfus believes that "competent performance is rational, proficiency is transitional; but only experts act rationally" [1]. He describes rationality as the ability to react without conscious analytic decomposition or reconstruction. He also uses the term conscious *calculative rationality* to describe the degraded level of skills typically associated with the ongoing enforcement of *know-that* rules. Similarly he promotes the use of *know-how* or *deliberative rationality* as a means of improving intuition, where time constraints and context will generally constrain the latter. It is clear that humans generally think *just-in-time*, although the expert may actually connect previous

[1] STEAM is a multi-agent system built on top of State, Operator And Result (SOAR) – 1987.

experiences with an imagined future. For instance, humans do NOT normally experience new situations in isolation. Humans typically adjust their perception based on a transition between one event and another. For this reason, they are seldom void of information when new problems manifest. As they learn, they also possess former experiences upon which they can reference or draw an associative response. Unfortunately, most AI research has evolved trying to solve problems associated with one of these micro or flat-world scenes, typically in isolation to all others.

Experts will describe their awareness using all environmental elements that appear within their visual focus, where a novice will typically react only to one or more of the component pieces. Experts respond to concepts, rather than simple chunks of information, for instance; the castled king's formation in chess. This form of intuition is hard to describe, because words (explanation) alone don't provide the cognitive links used by individuals to process subconscious concepts (rationalisation). Again, this similarity of symptoms must also be assessed within the context of the situation. The expert will seamlessly transform these abstract situations into concrete experiences by decomposing the environment into recognizable elements that can be associated with skills or behaviour that has worked in the past [1].

Boyd described a similar belief in his Observe, Orient, Decide and Act (OODA) cycle [17]. In this process, humans are required to focus on their observations and orient this to their internal beliefs before deciding or acting. More recently van Loon introduced the Stars approach that focuses on cognitive enhancement and decision-making at any point in the cycle of actions monitored using the following steps:

- Data collection;
- Sharing and analysing information;
- Transforming learned information into heuristic knowledge;
- Interpreting heuristic knowledge into concepts;
- Apply concepts to gain competencies;
- Integrating multiple competencies to develop expertise; and
- Perform expert actions to master expertise and be able to teach others.

The Stars cycle collects data, shares information, transforms learning into knowledge, interprets intelligence and competence, which is integrated as expertise. Mastered expertise is (re)injected and integrated with new information entering the system where the cycle continues promoting the utility of knowledge. This is a close approximation to how a Decision Support System (DSS) transforms environmental data into heuristic knowledge. This cycle highlights the need to transform information into cognitive concepts that may ultimately be expressed as seamless behavioural activities. Alternatively, Figure 1 depicts a visual representation of the Putzer and Onken approach to designing a cognitive system used to assist machines in mimicking human behaviour.

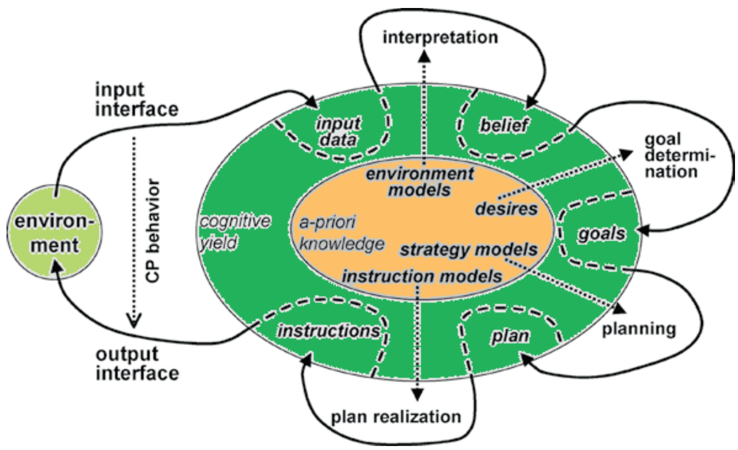

Fig. 1. The Cognitive Process [18]

The oval shaped body hosts the environmental data being processed (the center depicts the *a-priori* knowledge while the outer contain the Situation Awareness (SA) information) [18]. The information flows are transformed using situated processes within the dashed regions, with data being passed across the solid links in the direction of the arrows. The information is interpreted and matched against predetermined patterns prior to choosing a plan of action to ultimately realize a goal [19].

Software is used to implement these concepts and LISt Processing (LISP) was originally used to instantiate *predicated decisions* based on a series of periodically refreshed heuristic parameters. For instance PRS-Lite used less than 500 lines of LISP code in its executor [20]. A more complex system, label *PRS-Classic* was ultimately used to monitor the *Reaction Control System* on-board the Space Shuttle [21]. This form of decision-making has been labelled as *meta-level* reasoning, stimulating a number of popular systems, such as; PRS, Java Agent Compiler and Kernel (JACK), Battle Model [16] and R-CAST. These frameworks continue to evolve in an effort to increase the value of thought or cognitive decision-making achievable within machines.

3. Cognitive frameworks

Most early robotic control systems employed architectures that focused on marshalling lower-level processes to invoke desired behaviour [22]. These systems were able to perform discrete actions while conducting continuous processes (both goal or event driven). Heuristic logic has been used to process sensor data and maintain a digital representation of the observable environment (described as structured information). Cognitive frameworks allow designers to collect desired processes and embed the captured behaviour into platform control systems. Procedural knowledge was used to provide a natural and expressive framework to encode and validate task-level activities [20]. Unfortunately, the responsiveness of these systems relied heavily on the computational efficiency of the reasoning engine. This approach typically incorporated a sense-act cycle (perceive, interpret and control). Goals are semantically derived using a parametrised schema and the system responds automatically based on the success or failure of predicated rules [23]. A procedural list or sequence of declared tasks (called *intentions*) can be scripted to successively achieve tasks until the stated goals are satisfied. The level of success will be periodically measured against the internal beliefs of this reasoning system. The reasoning engine executes the activity schema by switching between top-level goals (nodes) in a ‘forest’ of *directed graphs* [22].

A cognitive architecture should provide a framework where physical symbolic systems can be realised [24]. It would provide definitions, resources, constraints and management processes needed to achieve cognitive processing. Table 1 lists a number of cognitive architectures that have had limited forms of success [25].

A suite of BDI [34] agent frameworks ensued in an attempt to increase the level of cognitive decision-making within machines. As suggested above, many sought to develop a form of perception that learns environmental information by mimicking human-like, cognitive behaviour(s) to solve realistic problems. This is a non-trivial task, because a human brain contains over 100 billion neurons. IBM and other researchers have managed to emulate limited aspects of brain activity using computers. Regardless of the cost or resources used to emulate a virtual mind, using this technology would consume the power of a medium sized town. For example, the Modular Neural Exploring Travelling Agent (MoNETA) Project was used to synthesize a small mammalian brain in 2010. This contained over 60,000 neurons and 120 million synaptic connections [35]. This success provides hope and organisations like the National Aeronautics and Space Administration (NASA) continue to monitor its progress.

NASA has kindled a paradigm shift in designing mission systems. This shift has occurred for many reasons, although it is generally attributed to design and maintenance costs. For example, the Galileo mission cost over US $1B and still requires a ground control/maintenance crew of between 100 - 300 people, 24 hours per day for the whole of its mission. Budget pressures offered no alternatives, therefore NASA endeavoured to transform to lightweight control systems. The only other alternative was to abandon the flight program altogether. Previously operators have monitored *tele-visory* links to maintain the decision-loop for machines. This fails to work when communications are interrupted or become intermittent. Similarly, the distance of space has induced significant temporal delays in the tele-presence control loop. This delay isolates the operator and removes the ability to take reactive control measures. NASA was subsequently forced to introduce a *virtual* capability to emulate the human presence and invoke time critical control decisions required during celestial travel. Their alternative was to exploit the Remote Agents (RAs) using AI conventions and implement embedded systems with tractable reasoning [36]. The design of the Mars Pathfinder (MPF) mission demonstrated an order of magnitude in savings. The new

Table 1. Early Cognitive Architectures

Year	Project	Subject Matter Experts	Example
1986	PRS	Georgeff, Lansky and Ingrand [20]	Shakey the robot - Classical planning (Deliberative Systems) and eventually PRS
1987	Soar	Laird, Newel and Rosenbloom [26]	Tac Air-Soar HBM - Production system to yield behaviour
1990	Prodigy	Carbonell, Knoblock and Minton [27]	DYNAMIC - Planning and Learning
1995	ICARUS	Langley, Cummings and Shapiro [28]	BlockWorld - Conceptual memories for problem solving and skill learning
1997	dMARS	d'Inverno, Kinny, Luck and Wooldrige [29]	Milou robot - Fuzzy Logic navigation and BDI environmental integration
1997	JACK	Georgeff and Lucas [30]	Jadex - Agent oriented implementation of BDI
1998	ACT(R)	Anderson and Lebiere [31]	jACT-R - Using declarative and procedural Knowledge processing (Rational Thought)
1999	Battle Model	Tildah [32]	WCME - Off-the-shelf DSS using monte carlo simulation and high fidelity scripted scenarios
2001	R-CAST	Yen, Yin, Ioerger, Miller, Xu, and Volz [33]	PrT Nets - Adaptive decision making and planning

paradigm created a significant challenge for scientists, because all previous on-board systems had no embedded intelligence. More ambitious projects require teams of distributed intelligent agents to operate remotely, such as the Cryobot Probe and Hydrobot Submercible, DS3 and the Martian pane.

A new Mission Planner was introduced to manage the fly-past of Europa. This platform had to operate up to twelve months without direct human interaction when it began exploring the Martian surface. To achieve the required autonomy, a New Millennium Autonomy Architecture Prototype (NewMAAP) agent was developed by a group of AI researchers in six months at NASA Ames and Jet Propulsion Laboratories (JPL). The new agent contained "integrated constraint-based planning and scheduling, robust multi-threaded execution, within a model-based identification and reconfiguration module" [36]. Four distinctive features were:

- long-term autonomous operation;
- guaranteed success based on tight deadlines and resource constraints;
- high reliability; and
- concurrent activities within tightly coupled subsystems.

This style of programming is based on observation by initially exploring the *breadth* to accommodate the functionality required in a given set of hardware. A *best-first* graph search algorithm was embedded into the kernel [37] to cater for a wide range of narrowly focused diagnostic plans. This was implemented in a Reduced Instruction Set Computer (RISC) approach to multi-threaded, goal directed execution. This avoids the creation of a brittle *mission profile* across parallel mission segments. Klein believes that operators respond symbolically using rate monotonic *thin slicing* to provide judgement or derive snap decisions [38]. He extends this concept of processing information gained through human based sensors using experiential patterns stored in our subconscious mind. Boyd further extends the human thought process to enable us to employ a control mechanism to focus on the goal, through OODA [39]. Being a closed loop system, stimuli can be used in place of observations in an OODA-based system to create a Stimulate Observe Decide and Act (SODA) framework, which works well within a known contextual environment [40]. Such issues predominantly surface during complex, hostile engagements. Especially in an environment where BDI can result in 'mode' confusion. Such confusion potentially compromises the desired goal [41]. To reduce this problem Rasmussen postulates that people use experiential ladders [42] based on the Rules, Skill and Knowledge (RSK) associated with the context of the environment (where each scenario should be extrapolated by Subject Matter Experts (SMEs)). Vicente studied this approach from the *work domain* analysis perspective, concentrating on the *cognitive domain* to derive the problem scope [43].

In 1992 Ingrand et al. introduced an alternate methodology called PRS [10]. They described this BDI approach to decision-making in a dynamic environment. The framework stores hierarchical procedures with conditions, effects, and ordered steps that invoke sub-procedures. Dynamic data structures store beliefs about the environment, while declarative rules contain desires that agent will attempt to achieve when the intentions the desired plans are executed. Figure 2 displays a high level view of the PRS framework.

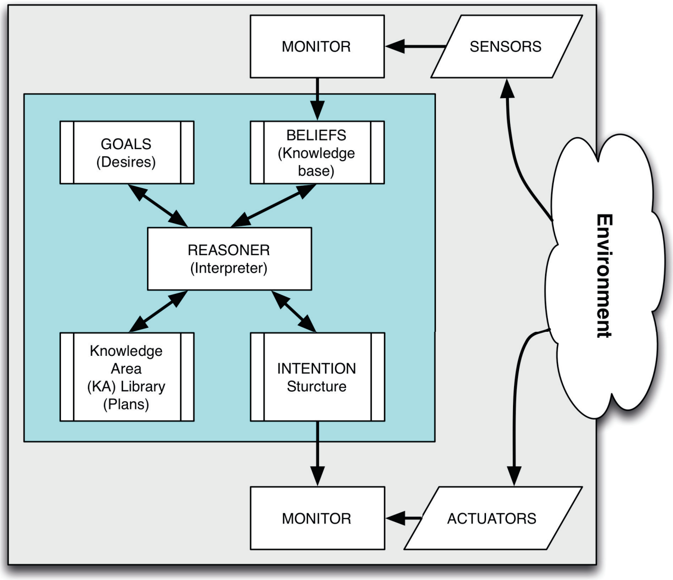

Fig. 2. Architecture for PRS [25]

This framework uses a periodic cycle to decide whether to continue executing its current intention or to select a new intention to pursue [44]. BDI frameworks also exist in distributed Multi-Agent Reasoning System (dMars) and JACK, however there is sufficient literature for the reader to pursue independent of the current paper. This paper proposes an adaptive system, based on a BDI framework, in preference to the end-means approach used by SOAR. To represent tele-visory control, a number of researchers integrated cognitive processes into Recognition-Primed Decision (RPD) models with agents [33] to capture the decision making abilities of domain experts based on the recognition of similarity between the current situation and past experiences. That is matching *features* with *symbolic cues* to build a *story*. The recognition phase of decision making requires the development of a process that generates a local view of situation awareness. Once oriented to the current environment, *courses of action* can be determined from which decisions can be chosen. Subsequent rounds in the decision-making cycle continue to evaluate alternative courses of action prior to choosing the most appropriate action. Klein developed a model based on a team setting that resulted in an RPD-Agent architecture. This architecture consists of four modules [45]. The communication manager module governs the inter-agent communication and organises conversations. The expert system module is a rule-based forward chaining system. It contains knowledge related to the other agents and external world. The process manager module is responsible for scheduling and execution of plans. The collaborative RPD module facilitates the collaboration of humans and RPD agents.

Developers of modern RPD-Agents generally use R-CAST because the state and functionality are well suited to Agent Oriented Programming (AOP). Figure 3 shows how agents can be used to embrace a scalable architecture. This software has been tested within a military command-and control simulation, involving intelligence gathering, logistics and force protection. Under normal time pressures, human teams make the correct decisions about a potential threat. But when subject to time constraints, the same teams' performance may suffer due to the lack of information sharing. This may result in incorrect decision making about whether to attack or avoid the incoming

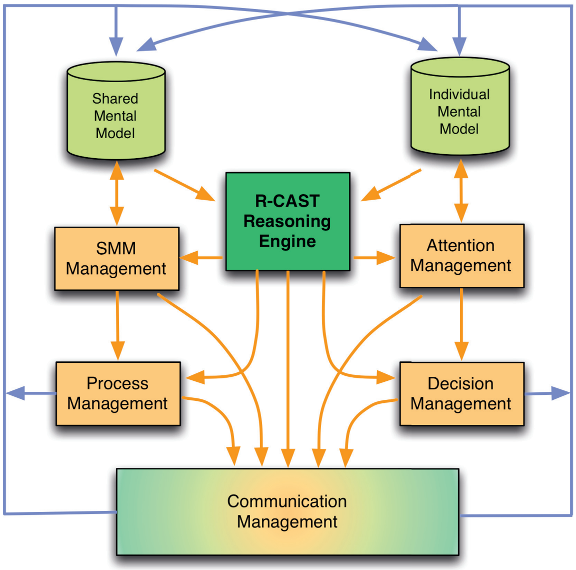

Fig. 3. R-CAST: RPD-enabled Agent Architecture [46]

threats. The researchers have demonstrated that the R-CAST agent systems helped the human agent in making the right decision under time pressured conditions [47]. As suggested, other frameworks exist and many achieved limited success, although none have an enduring outcome. The current paper proposes a hybridised approach, which is discussed next.

4. Proposed cognitive mission system

Researchers have shown that it may be possible to combine a scientific understanding of the brain with improved parallel processing techniques in software to enhance higher-order decision making within machines. Future cognitive architectures will continue to rely on improvements in Computational Intelligence (CI) techniques, especially AI and Machine Intelligence (MI). Previous designs have failed to endure. Given that the problem space is complex and the environment is often continuously changing, constraints are imposed to determine repeatable results. Most are focused on attempts to map or reproduce human-like functions and procedures. It may be possible to stimulate machines to provide event-based responses without the need to duplicate or mimic human cognition, however there is a real need to provide recognition, learning, memory (persistent and temporal), reasoning and rationality. These represent the key attributes that must be pursued using a three dimensional approach (events, kernel behaviours and decision-making). This is to simultaneously monitor events, kernel behaviours and implement higher-levels of decision-making, while processing requests, coordinating the mission and adapting to environmental changes.

Given the amount of research and techniques to be discussed or evaluated, this paper simply highlights a number of appropriate concepts that require significant consideration. These concepts are derived from techniques used in machines that were previously developed for other purposes, by a divergent collection of skills and expertise. Some of these machines have fixed *form* and *function*, where many more modern machines are mobile and expected to operate in dynamic environments. Many of these focus on attempt to personify human behaviour within machines. At least seven of these approaches have reported limited success. For instance PRS, SOAR, Prodigy, ICARUS, dMars, JACK, Adaptive Character of Thought–Rational (ACT-R) and R-CAST. They involve creating control systems, rules to implement constraints, logic to make low-level decisions (logic), memory models to build situation awareness and expert systems to implement corporate knowledge. The facts would traditionally be decomposed by humans and preloaded into the systems memory model before execution. Similarly, all learning would be validated externally before being appended to the existing knowledge repository for re-use during other missions. These all rely on a mission controller seeking to complete a goal, based on inferred facts that are derived from heuristically modified knowledge (stored on-board in local databases). The need for each has already been reported in existing literature, however a brief synopsis of these concepts include, but are not limited to:

- Communication between humans (intent) and machines (goals) is an enduring pursuit.
- Knowledge is presented, represented, verified, stored and retrieved in many forms.
- Memory can be represented in many ways, have a varying degree of significance and temporal usefulness. Several labels to be investigated include: declarative, heuristic, episodic, short-term (environmental and task oriented information) long-term (environmental and goal oriented information) and procedural memory.
- BDI must be implemented using a contextual record-set, using task oriented modality that will be determined via external sources.
- The cyclic approach to monitoring the status of the whole system uses a rate monotonic schedule to update state information. This three dimensional kernel prosecutes a prioritised list of pre-emptive processes in manageable chunks to execute the actions being prescribed during the status checks. The kernel runs a 'reactor' thread to monitor system signals and events to coordinate mission goals during the conduct of its decomposed tasks.

More research needs to be done in order to determine whether any existing techniques can be re-used, integrated or implemented at scale within the proposed cognitive mission systems. Figure 4 displays a schematic of a number of concepts that may provide higher-levels of cognitive decision-making on-board the platform. An holistic approach calls for a design that considers transforming human *intent* into a programmatic format that is capable of achieving the decomposition of goals for the desired concepts. The OODA loop has successfully been used externally to focus human cognition. These have been encoded as BDI concepts to control machines (internal state/behaviour space). The hardware must operate using a real-time operating system that is pre-emptive and sufficiently parallel in nature to process thousands of micro-threads independently. There is no doubt that

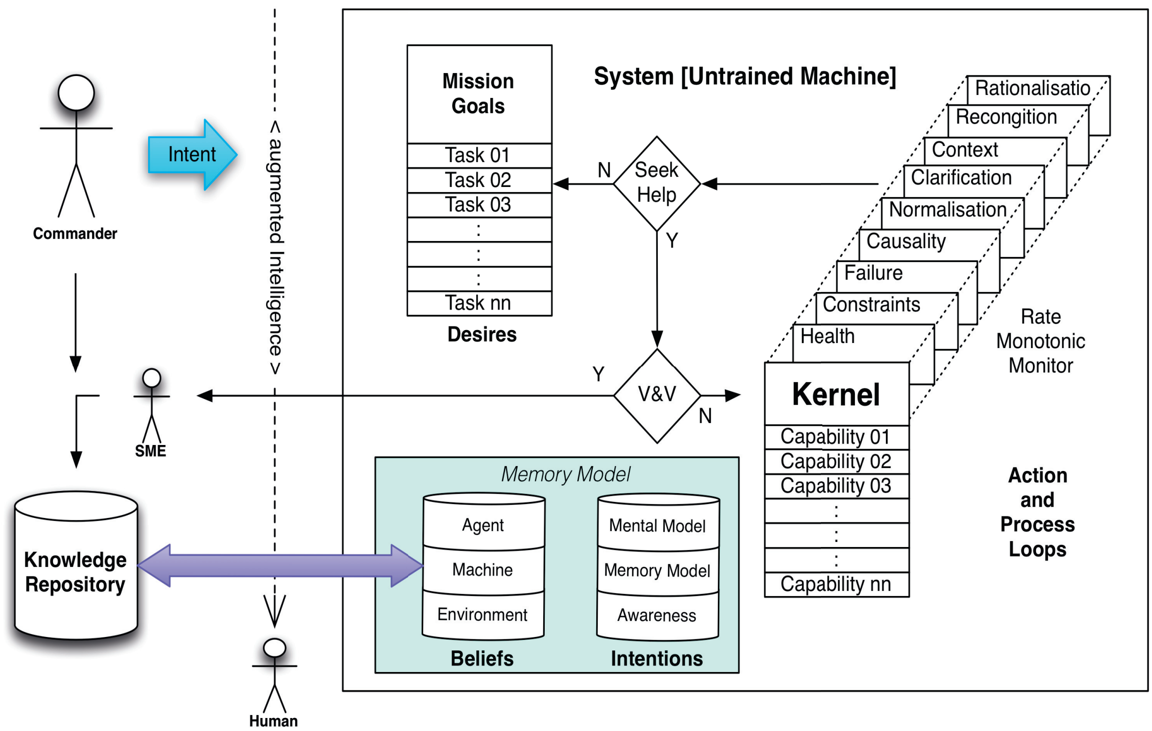

Fig. 4. Proposed Cognitive Mission Systems

a production system should be used to manage the mission goals, a memory model is required to represent and manage the system's state of mind (virtual-psyche) and a belief system to maintain the system's rationality. As with all knowledge repositories, data, information, rules and assertions must to be verified and validated prior to being included into the collection. In contrast, a machine will often fail due to missing or imprecise information or directions. A mechanism is required to enable the reasoning system to request additional information to clarify either the operator's intent or the mission objectives (desires). Finally a multi-dimensional action process loop is introduced to influence and monitor simultaneously. Global variables and system flags can be updated during a rate monotonic loop (every system cycle). These would influence how and when each capability executes. Independently, more capable sensors are used in a similar fashion to provide environmental information directly to the mental model. The reasoning system is then free to reflect on the system's operation and react accordingly.

5. Conclusion and future research

This paper highlights a number of the more successful concepts that could be used to generate a new approach to cognitive decision-making. The future is uncertain and more research is required to verify which elements of previous frameworks should be preserved and re-used. The integrated functionality should focus on an emerging solution and stimulate a more collaborative solution. It is clear that existing effort has NOT provided an enduring outcome. Similarly the recent shift to a more autonomous workforce has created an environment were solutions are being actively pursued to reduce *synthetic automation*, currently provided by humans who remotely provide the desired functionality.

This paper raises many issues and attempts to combine a number of pre-existing advanced knowledge representation concepts. The NASA example shows where significant effort is still required to emulate new capability and support existing earth bound facilities, especially in during isolated or uncertain conditions. New technology using multi-threading techniques may fundamentally improve speed and scale required to champion internally or externally distributed software execution. The use of a micro-kernel concept with independent threads will enable compartmentalised state processing and enabled perceived behaviour to be pursued as outside of the kernel operations. This paper provides an outline of historical attempts to achieve human-like decision-making. It concludes with a conceptual idea that is hoped to stimulate discussion and entice further collaboration by subject matter experts that ultimately generates more human-like decision-making within machines. Future research effort should focus on the success stories and lessons learned, prior to creating components for use in future designs.

References

[1] H. L. Dreyfus, S. D. Dreyfus, Mind over machine: The power of human intuition and expertise in the era of the computer, Blackwell, Oxford, UK, 1986.

[2] J. McCarthy, Programs with common sense, in: Symposium on Mechanization of Thought Processes, National Physical Laboratory, Teddington, England, 1958.

[3] H. A. Simons, The Shape of Automation: for Men and Management, Harper and Row, New York, NY, 1965.

[4] P. McCorduck, Machines Who Think: A Personal Inquiry into the History and Prospects of Artificial Intelligence, W. H. Freedman, New York, 1979.

[5] J. L. Lunn, Chick sexing, American Scientist 36 (1948) 280 – 287.

[6] P. Benner, Five step - From Novice to Expert: Excellence and Power in Clinical Nursing Practice, Addison-Wesley, Menlo Park CA, 1984.

[7] H. van Loon, Reach for the stars: Best practice, in: Quality Progress, American Society for Quality, Milwaukee, WI, 2007, pp. 38 – 42.

[8] K. Konolige, K. Myers, E. Ruspini, A. Saffiotti, The saphira architecture: A design for autonomy, Journal of Experimental and Theoretical Artificial Intelligence 9 (1997) 215 – 235.

[9] H. Moravec, A. Elfes, High resolution maps from wide angle sonar, in: IEEE International Conference on Robotics and Automation, Vol. 2, 1985, pp. 116 – 121.

[10] F. F. Ingrand, R. Chatila, R. Alami, F. Robert, PRS: A high level supervision and control language for autonomous mobile robots, in: Proceedings of the IEEE International Confonference on Robotics and Automation, Minneapolis, 1996, pp. 43 – 49.

[11] M. d'Inverno, M. Luck, M. Georgeff, D. Kinny, M. Wooldridge, The dMARS architecture: a specification of the distributed multi-agent reasoning system, in: Autonomous Agents and Multi-Agent Systems, Vol. 9, Kluwer Academic Publishers, Netherlands., 2000, pp. 5 – 53.

[12] AOS, JACK Intelligent Agents: Teams User Manual, Agent-Oriented Software, Carlton, Melbourne, release 4.1 Edition (March 2006).

[13] AOS, JACK Intelligent Agents: Users Manual, Agent-Oriented Software, Carlton, Melbourne, release 4.1 Edition (2004).

[14] N. R. Jennings, Controlling cooperative problem solving in industrial multi-agent systems using joint intentions, Artificial Intelligence 75 (2) (1995) 195 – 240.

[15] M. Tambe, Towards flexible teamwork, Journal of Artificial Intelligence Research 7 (1997) 83 – 124.
[16] G. Tidhar, C. Heinze, M. C. Selvestrel, Flying together: Modelling air mission teams, Applied Intelligence 8 (3) (1998) 195 – 218.
[17] G. T. Hammond, The Mind of War: John Boyd and American Security, Smithsonian Institution Press: Washington, USA., 2004.
[18] H. Putzer, R. Onken, Cosa: A generic cognitive system architecture based on a cognitive model of human behavior, Cognition, Technology and Work 5 (2) (2003) 140 – 151.
[19] A. Waesdorf, H. Putter, R. Onken, The cognitive process and its application within cockpit assistant systems, in: Intelligent Transportation Systems, IEEE, New York, 1999, pp. 874 – 879.
[20] M. Georgeff, A. Lansky, Procedural knowledge, in: N. G. Leveson (Ed.), IEEE (Special Issue on Knowledge Representation), Vol. 74, 1986, pp. 1383 – 1398.
[21] M. Georgeff, F. Ingrand, Decision-making in an embedded reasoning system, in: Eleventh International Joint Conference on Artificial Intelligence, Vol. 2, 1989, pp. 972 – 978.
[22] K. Myers, A procedural knowledge approach to task-level control, in: Third International Conference on Artificial Intelligence Planning Systems, AAAI Press, Menlo Park, CA, 1996, pp. 158 – 165.
[23] A. Saffiotti, K. Konolige, E. H. Ruspini, A multivalued logic approach to integrating planning and control, Artificial Intelligence 76 (1–2) (1995) 481 – 526.
[24] N. J. Nilsson, The physical symbol system hypothesis: Status and prospects, in: 50 Years of AI, Vol. 4850 of LNAI, Springer, Berlin, 2007, pp. 9 – 17.
[25] J. W. Tweedale, Using mutli-agent systems to improve the level of autonomy for operators controlling unmanned vehicles, in: M. Graña, C. Toro, J. Posada, R. J. Howlett, L. C. Jain (Eds.), KES, Frontiers in Artificial Intelligence and Applications, IOS Press, 2012, pp. 1666 – 1675.
[26] J. Laird, A. Newell, P. Rosenbloom, Soar: architecture for general intelligence, Artificial Intelligence 33(1) (1987) 1 – 64.
[27] J. Carbonell, O. Etzioni, Y. Gil, R. Joseph, C. Knoblock, S. Minton, M. Veloso, PRODIGY: an integrated architecture for planning and learning, Intelligence/sigart Bulletin 2 (1991) 51 – 55.
[28] P. Langley, K. B. McKusick, J. A. Allen, W. Iba, K. Thompson, A design for the icarus architecture, SIGART Bulletin (1991) 104 – 109.
[29] M. d'Inverno, D. Kinny, M. Luck, M. Wooldridge, A formal specification of dmars, in: M. P. Singh, A. S. Rao, M. Wooldridge (Eds.), Agent Theories, Architectures, and Languages, no. 1365 in Lecture Notes in Computer Science: Intelligent Agents, Springer-Verlag, 1998, pp. 155 – 176.
[30] N. Howden, R. Rönnquist, A. Hodgson, A. Lucas, Jack intelligent agents: Summary of an agent infrastructure, in: 5^{th} International Conference on Autonomous Agents, Agents2001, Montreal, Canada, 2001, pp. 1 – 4.
[31] J. R. Anderson, Rules of the Mind, Erlbaum, Hillsdale, NJ, 1993.
[32] P. Dart, E. Harris, P. Malkin, M. Selvestrel, G. Tidhar, Guidelines for integrating a model with the BattleModel architecture, Tech. rep., Defence Science and Technology Organisation, Fishermans Bend, Australia (2002).
[33] J. Yen, J. Yin, T. R. Ioerger, M. S. Miller, D. Xu, R. A. Volz, CAST: Collaborative agents for simulating teamwork, in: IJCAI, 2001, pp. 1135 – 1144.
[34] A. Rao, M. Georgeff, Bdi agents: From theory to practice, in: 1^{st} International Conference on Multi-Agent Systems (ICMAS'95), San Francisco, CA, 1995, pp. 312 – 319.
[35] M. Versace, B. Chandler, The brain of a new machine, IEEE Spectrum, Institute of Electrical and Electronics Engineers, New York 47(12) (2010) 28 – 35.
[36] N. Muscettola, P. P. Nayak, B. Pell, B. C. Williams, Remote agent: To boldly go where no AI system has gone before, Artificial Intelligence 103 (1–2) (1998) 5 – 47.
[37] B. C. Williams, P. P. Nayak, A model-based approach to reactive self-configuring systems, in: J. Minker (Ed.), Workshop on Logic-Based Artificial Intelligence, Washington, DC, June 14–16, 1999, Computer Science Department, University of Maryland, College Park, Maryland, 1999, pp. 971 – 978.
[38] C. S. Dodson, M. K. Johnson, J. W. Schooler, The verbal overshadowing effect: why descriptions impair face recognition., Mem Cognit 25 (2) (1997) 129–139.
[39] R. Coram, Boyd: The Fighter Pilot who changed the Art of War, Little Brown and Company, Boston-New York-London, 2002.
[40] J. W. Tweedale, L. C. Jain, Embedded automation in human-agent environment, Vol. 10, Springer, Berlin, Heidelberg, 2011.
[41] M. E. Bratman, What is intention?, in: P. R. Cohen, I. L. Morgan, M. E. Pollock (Eds.), Communications, MIT Press, Canbridge, MA, 1990, pp. 15 – 32.
[42] J. Rasmussen, Information Processing and Human-Machine Interaction: An Approach to Cognitive Engineering, Elsevier Science Publishers, 1986.
[43] K. J. Vincente, CongnitiveWork Analysis: Towards Safe, Productive and Healthy Computer-Based Work, Lawrence Erlbaum Associatesn, Mahwah, NJ, USA, 1999.
[44] P. Langley, J. E. Laird, S. Rogers, Cognitive architectures: Research issues and challenges, Cognitive Systems Research, Elsevier, Amsterdam, The Netherlands 10 (2009) 141 – 160.
[45] X. Fan, S. Sun, J. Yen, On shared situation awareness for supporting human decision-making teams, in: AAAI Spring Symposium on AI Technologies for Homeland Security, Stsnford, CA, 2005, pp. 17 – 24.
[46] X. Fan, S. Sun, B. Sun, G. Airy, M. McNeese, J. Yen, T. Hanratty, J. Dumer, Collaborative rpd-enabled agents assisting the three-block challenge in command and control in complex and urban terrain, in: Conference on Behavior Representation in Modelling and Simulation ((BRIMS), University City, CA, 2005, pp. 113 – 123.
[47] T. Hanratty, J. Dumer, J. Yen, X. Fan, Using agents with shared mental model to support objective force, in: Cybernetics and Informatics (SCI 2003), 7th World Multiconference on Systemics, Orlando, USA, July 2003, pp. 27 – 30.