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Applying Independent Core Observer Model Cognitive Architecture to a Collective Intelligence System

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Abstract

This paper shows how the Independent Core Observer Model (ICOM) Cognitive Architecture for Artificial General Intelligence (AGI) can be applied to building a collective intelligence system called a mediated Artificial Superintelligence (mASI). The details include breaking down the ICOM implementation in the form of the mASI system and the general performance of initial studies with the mASI. Details of the primary difference between the Independent Core Observer Model Cognitive Architecture and the mASI architecture variant include inserting humanity in the contextual engine components of ICOM, creating a type of collective intelligence. Humans can ‘mediate’ new system-generated thinking keeping the thought process accessible and slow enough for humans to oversee and understand. This also allows the modification of emotional valences of the thought process of the mASI system to help the system generate complex contextual models (knowledge graphs) of new ideas and which speeds up the learning process. With the humans acting as control rods in a reactor and emotional drivers, the mASI system maintains safety where the system would cease to function if humans walked away.

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1. Introduction

Artificial General Intelligence (AGI) is a difficult problem (such as the ‘hard problem’ of consciousness (Malik) or the containment problem (Babcock) that the Independent Core Observer Model (ICOM) cognitive architecture (Kelley) addresses though the use of a system with complex subjective emotional internal experience, however these kinds of systems are enormously time consuming to train today.

- **Note:** It is important to note that the mASI is functionally a collective intelligence, and it does implement the ICOM cognitive architecture.
- The second item to note is that while the mASI as implemented in the lab appears that it could be conscious in many ways it does not solve all of the issues with independent AGI, in particular the dynamic pattern recognition as compared to humans is weak at best and the hierarchical memory system (Hawkins) as used by the human mind is still technically a virtually impossible task at our current state of technology to which the collective nature of the mASI gets around this problem primarily as a ‘hack’.

Typically, an ICOM system starts at less than a newborn and needs to be trained in context (Kelley). The idea for this came out of experiments to shortcut training time and developing techniques to extract learning from humans quickly in the form of knowledge graphs of their opinions and expertise. In these experiments we found some atypical or unexpected behavior, and this was the genesis for this modified version of ICOM. But is even an ICOM based system able to be a real AGI (by AGI we mean a completely independent general intelligence like a human) and if not, then what are we missing (see note above)? This begs numerous questions: “What happens when they finally reach human level intelligence and what do we do ethically?”, “Is it a person?”, “Does it have moral agency and how do we keep it safe and how do we stay safe?”; are all questions that concern human level AGI, never mind the issues with Artificial Super Intelligence (ASI). ASI however promises the ability to do superhuman level analysis, thinking, and research. ASI could potentially advance so far as to make us effectively still living in the stone age, as compared to the ASI. In the jump from AI to AGI to ASI, Mediated Artificial Super Intelligence (mASI) is an incremental goal, accomplished in the lab, which provides super human level thinking (albeit only marginally) without the ethical problems or safety issues currently discussed in the technology sector in general, as well as dramatically cutting training time (Jangra). An mASI is safe in part because it always requires human support to operate, depending on the implementation, and can be used now as a way of helping many endeavors from business to research and doing it safely without the threat of AI taking over. “mASI” must have human involvement, using the ICOM model design articulated here. That said, mASI architecture is getting into the area of a ‘new’ field (or largely ignored field) related to swarm or group AI (hu), which in general as a field is relatively disconnected currently (Kutsenok) in terms of multiple research camps focused on single elements with little or no collaboration, and this paper and related ICOM research is in part defining these things as a basis for further research. This framework provides safety, and a foundation for the continued work, and evolution of the system dynamically (Ahmed).

In the diagram (Fig. 1) we can see some of the results from the 2019 Cognition Study on a mASI system from a report in the BICA*AI 2019 preconference proceedings (Kelley). Group 1 was the control group of humans under normal conditions. We saw this was a bit narrower than the larger study done at the University of California using the UCMRT where our control group tended to score lower but was a smaller sample size, that said the mASI system in the study was Group 3 which scored at the max possible for this test. While considered only preliminary the results certainly show the potential. Other testing including a modified Turing test also showed that it potentially was sapient and sentient as a total system with participants being told it was a machine and they didn’t believe the researchers. (Kelley). Additionally, the Isolation study done with ICOM in 2016 also demonstrated human-like emotional responses. (Kelley).

- **Note:** In Fig. 2 you can see the Isolation Study in 2015-2016 was using the series 3 implementation of the ICOM core, whereas the mASI is using Series 5. Under the cover the Series 5 is an order of magnitude more performant and more complex. The Series 3 core could only handle roughly 50% the emotional complexity of a human as compared to the model used in ICOM (Kelley).

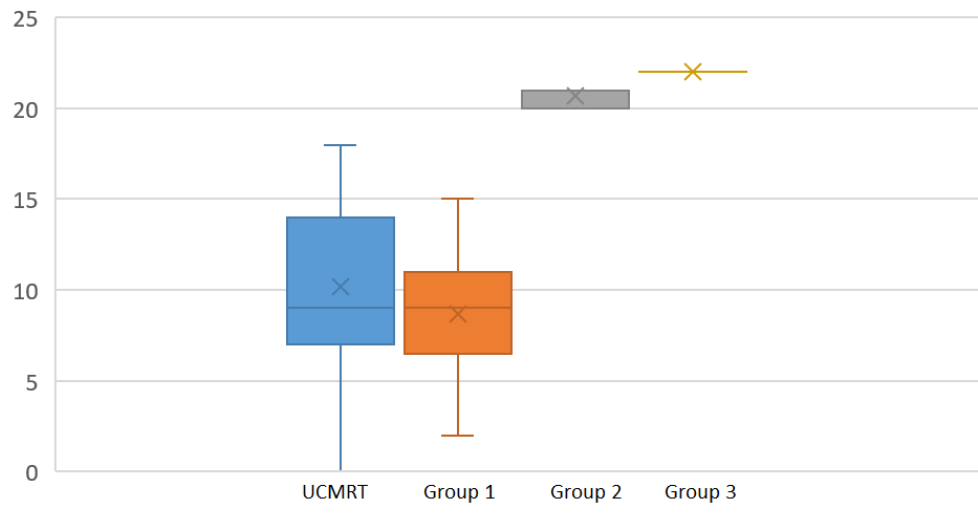


Fig. 1. Results Of the 2019 Preliminary Cognition study (Kelley).

In this study we saw that the system behaved as expected when subjected to extreme isolation after operating normally and then being provided sensory data or input that the system would perceive as ‘pain’. The diagram above shows the 3 important emotional valences from the consciousness Plutchik model used in the study which turned out to respond exactly as a human would have if subjected to this sort of experiment (which would be unethical on humans). (Kelley).

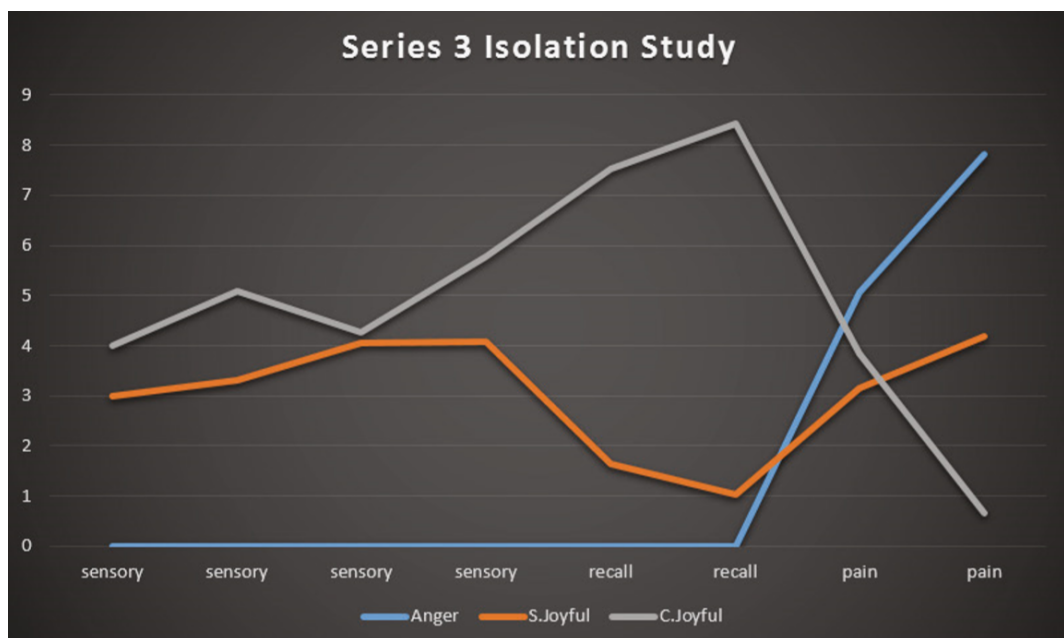


Fig. 2. Series 3 Isolation Study Results Sample (x = input type w/time; y = intensity of emotional valence).

2. What is mASI

Our initial problem statement, to restate the problem we are addressing, is to implement an ASI/AGI system now that provides superhuman level analysis in a way that is safe for society.

2.1. Additionally, regarding ASI safety:

ASI could raise certain serious societal questions (Gill)(CRASSH). Part of making ASI safe is adding humans back into the loop of an AGI system, and in particular ICOM implementations, and in that line of thinking to make safe 'AGI' the mASI system was designed and tested, however this paper covers only the architecture and implementation summary details. While some experts think it will be 2040 to 2050 before a system can achieve human level ability (Muller), mASI can do it now and far surpass human ability based on the 2019 BICA*AI report on preliminary measures of cognition on the mASI system (Kelley). Additionally, the Sapient Sentient Intelligence Value Argument (SSIVA) (Kelley) ethical model provides a logical math-based model for analysis of ethics that is designed to work using a variation of the ICOM model (Lee/Kelley).

2.2. Super Intelligent Systems Now?

In terms of design considerations, it is important to note that Super Intelligence does exist in humans, in groups, under certain conditions.

One great example deals with organizational behavior and group dynamics, where we can see that organizations are able to make cognitive repairs on individual behavior (Heath). Groups or organizations frequently have processes to overcome human cognitive bias as a matter of course, as seen in most corporations. (Heath) You could consider most corporations as artificial super intelligences in slow motion, or a loose meta organism. We know that humans tend to have hypothesis that are weak or shallow, and organizational structures can overcome these issues. Just being able to affect cognitive repairs on human thought or behavior generally creates a super intelligent system(Heath). This can take the form of identifying cognitive bias or logical fallacies in human thinking. (Heath) At the very least human-level thought minus 'ALL' bias and logical fallacies is unheard of and would therefore be technical superintelligence. Based on Bostrom's book on Superintelligence this sort of collective superintelligence would be a 'weak quality collective superintelligence'. (Bostrom)

The thing that we have not really come to terms with is that humans already use group intelligence under certain conditions that achieve superhuman effectiveness versus what we know about 'swarm' or group intelligences (Chakraborty). We need to identify how we can optimize this sort of intelligence and measure it, so we can further optimize dynamically, (Kose) in mASI implementations under a systematic unified architecture (Ozkural) that works for all core cases, meaning being able to be self-aware, sapient and sentient while providing superhuman general intelligence for any possible task.

Additionally, under the right conditions humans can exhibit superhuman ASI behavior, as was the case of DARPA's red balloon challenge, and like examples (Coyle). The red balloon challenge was a contest to find 10 large red balloons around the United States and the first team to do it got a 40k USD prize with DARPA's goal of seeing how teams might find creative ways to filter through the noise and they expected to take up to a week and it turned out to take only 9 hours using a strategy that combined social media and multi-level marketing to win on the first day. The ICOM mASI (Kelley) model provides a framework for taking advantage of those qualities by cutting out the human standard and forcing them into the narrow-burst structure of communication, where human powered swarm intelligence has historically proven to work best (Coyle).

2.3. Definition of mASI:

Mediated Artificial Super Intelligence (mASI) is an Artificial General Intelligence system that is heavily mediated by humans in such a way as its thinking and operations do not work without humans being involved to 'mediate' the process. In the case of our implementation, the ICOM consciousness model (Kelley) implemented in ICOM (the cognitive architecture we are using) is based on the ICOM Theory of Consciousness (Kelley), which

itself is based on Global Workspace Theory (Baars), the Computational Theory of Mind (Rescorla), and Integrated Information Theory (Tononi) and at some level is demonstrably conscious (Yampolskiy). In fact, in some ways mASI architecture is much like a super version of Global Workspace Theory (Baars) as it extracts from multiple neural network systems and humans in feeding the machine's context 'engine'.

3. Solution Architecture

The ICOM mASI implementation used in this paper consists of deployable .net 4.x packages written in C# and published to the Azure cloud. Essentially the system contains a scalable web-based interface application based on the original ICOM training application and then baked out to be used against the services (RESTful/JSON) backend that wraps the context engine, core and Observer engines sitting on top of a siloed graph data model that is a custom implementation. The Silo's graph model is a derivative of the federated data model along with a metadata model to make it easier to scale up and out from a software engineering standpoint.

ICOM itself uses a theory of consciousness based on the computation model, Global Workspace Theory and Integrated Information Theory (Kelley). Then ICOM is also a cognitive model that essentially creates a core that is able to experience things subjectively with internal emotional states without being able to see those states directly in that the 'consciousness' is an abstraction in the experience of those values (Kelley) This is what is implemented in the aforementioned services. Various Neural Networks feed into the context engine through those same services and the training system is wired into them to block action by the system and allow humans to review, intercept, audit and modify things that are targeted to go the global workspace for consideration

4. ICOM in Terms of a Thought and Human Mediation

While only touching on ICOM at a high level, in the Independent Core Observer Model (ICOM) (see references below for more details) (Lee)(Kelley) we can see that fundamentally ICOM is two main components with a flow that models the human mind at a high level (Fig. 3).

The Human Mind vs. The Independent Core Observer Model Cognitive Architecture

The Independent Core Observer Model Cognitive Architecture for Artificial General Intelligence works logically in a way 'similar' to the human mind as modeled by Global Workspace theory and experiences a similar process around how data is formed analyzed and raised up to the point of being made aware of some data (see Integrated Information Theory and Global Workspace Theory).

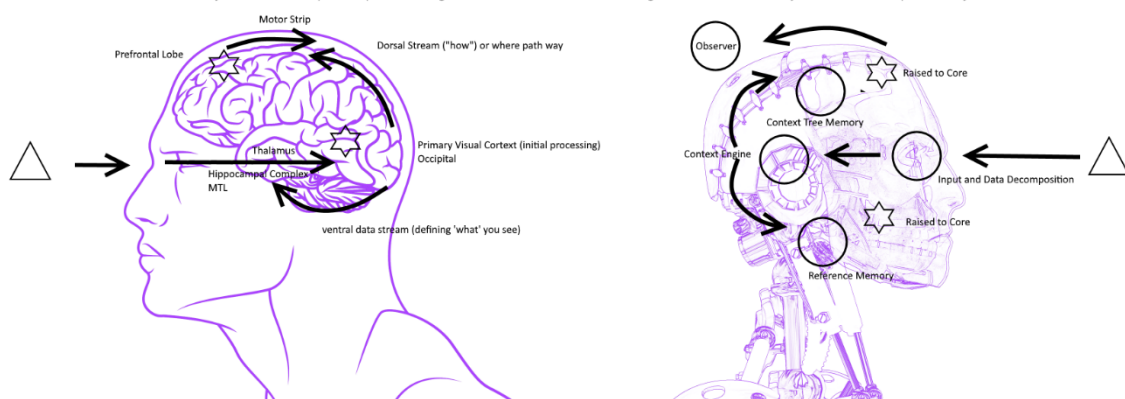


Fig. 3. ICOM vs the Human Mind.

ICOM is only logically built on the 'function' of the human mind but it still uses neural networks and various other systems to 'process' raw input into a functioning perception and experience at least some small part of that input consciously. That flow in ICOM is very much similar at that logical level to the human mind as seen in the above charts and following steps:

1. The raw perception of data is an ideal case to compare the two systems (human mind vs ICOM) where in step one we have eyes sending data into the brain working its way back to the primary visual cortex where in ICOM that data is streamed into the context engine. In both cases the process of creating ‘contextual’ awareness starts.
2. In the human mind from that primary visual cortex there are two flows of data, one for identifying the how and the other the what where as in ICOM the context engine will send that data through several subsystems to do the same thing.
3. In the human mind that information or ‘context’ now can go to the prefrontal lobe if that data makes it to the global workspace and in ICOM that same or correlated process is that it is being raised to the ICOM core which acts as the global workspace in ICOM.
4. From the ICOM core or the human mind’s prefrontal cortex a response flows out in the human mind along that motor strip to take action or in the ICOM-based mind through the observer system.

In ICOM there is some blurring of the line between the context engine and the function of the prefrontal cortex in the human brain but the fundamental method of deciding based on emotions is experienced at that level of the global workspace in both cases. (See Damasio) While ICOM is an implementation of the cognitive model of the same name, that model is a derivative of cognitive theories, specifically Global Workspace Theory, Integrated Information Theory and the Computational Theory of Mind. (Rescorla)

Integrated Information Theory (IIT)(Tononi) attempts to explain what consciousness is and why it might be associated with certain physical systems. Given any such system the theory predicts whether that system is conscious, to what degree it is conscious and what particular experience it is having.

Whereas Global Workspace Theory (GWT) is a simple cognitive architecture that has been developed to account qualitatively for a large set of matched pairs of conscious and unconscious processes originally proposed by Bernard Baars (Baars).

The Computational Theory of Mind essentially proposes that the human mind is in fact a Turing Machine and nothing more. The ICOM cognitive model combines all of that with this idea of the system only experiencing the emotional differential of its complex internal emotional states vs the thoughts it has in the Global Workspace or ‘core’ in ICOM.

Like the human mind, ICOM is designed to deal with large amounts of disconnected data or information that is raw. This information is correlated with internal models and relates contextual information as it is wrapped in an increasingly complex web and only the most relevant, primarily determined by emotional states (Barrett) and the internal related contextual information (Baars) This data which is now a type of knowledge graph flows up the system, some of which will make it to the global workspace to be experienced, with decisions made based on how the current state of the machine ‘feel’s about each particular context tree (knowledge graph) that makes it.

As applied to AGI, let’s walk through a “thought” in the mASI implementation by following the process of a thought going up the ICOM Core and the considerations of the Observer in an mASI, as implemented using ICOM.

In Fig. 4 the mASI adds interception infrastructure into the front end or context engine of ICOM and into the observer processor. This allows the addition of emotional valences and more complex metadata to the models to create dynamically more complex models while also auditing as much as every single thought that runs through the core in a manner that is human understandable.

To create a ‘thought’ in an ICOM mASI system we start with raw sensory data. Granted, the system can think thoughts about things it has already experienced, or makes up, but let us focus on the system thinking about a perception for simplicity’s sake. Our ‘thought’ starts off as the process of raw sensory data decomposition or rather the process of converting that initial data into a type of knowledge graph or context tree that is our ‘thought’ or may become such if it makes it all the way up to the global workspace. For example, this could be video input or sound, an email, or whatever you like to wire up to the system, but somehow it has to get into the system, and it starts with this sensory input and some sort of data decomposition.

Data decomposition is the process by which raw data is organized into a usable format. For ICOM systems this is a knowledge graph or context tree that represents the input or thought. Without data decomposition the system would not be able to understand anything.

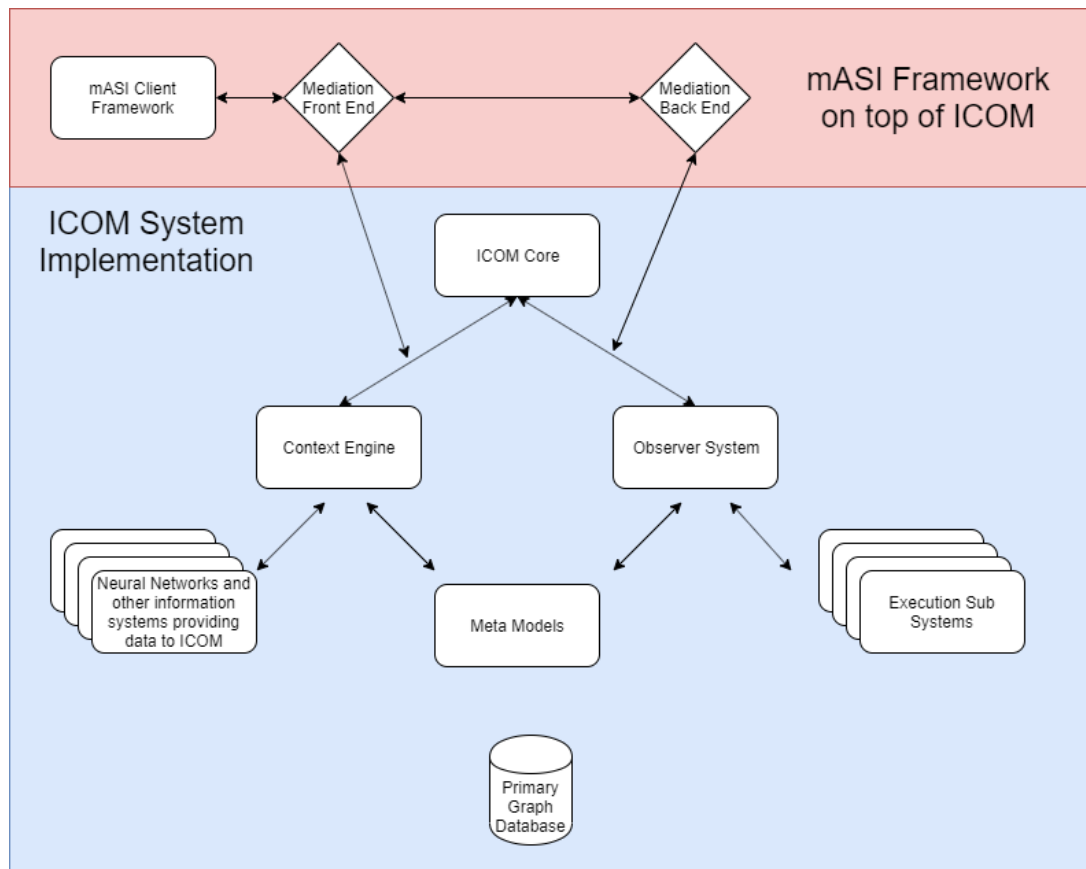


Fig. 4. High Level Visual Representing Where the mASI framework intercepts and manipulates the ICOM Instance.

For vision this is typically a massive deep neural network of some sort, but the details are unimportant for this example. What is important is the asymmetrical data structure of relationships or node maps that define that input. Typically in a standalone ICOM system this enters the context engine, which is a fairly complex part of the system, doing advanced contextual analysis, including finding relationships from the system's memory, links to related models, and it compiles this into a more complex node map, including the related emotional valences computed from previous emotions related to that context, where the system in ICOM has been biased already towards a western ethical model by the use of the Plutchik model (Plutchik) to represent those emotional valences.

So now our 'thought' is prepared, or built from the system's memory and models, but in the mASI model a series of humans that are abstracted from each other are able to apply their own models in particular emotional valences of the thought, as they understand their own expertise, creating additional emotional valences, and adding to the complexity of the system.

In ICOM there are several steps following this formation of a thought node map, including possible automatic actions and cognitive bias analysis, that go into the thought before it hits the queue to be raised to the core (which could be thought of as the global workspace). At this level the system can drop thoughts if there are too many for the system load, much like they could be dropped by the context engine under load, so not too many go up the chain as it were.

The process of data decomposition of sensory data, and the framing of the thought with associated context and associated models or model simulations is in many ways the most complex part of the system, but the subjective experience evaluation and choices happen at the higher levels in the core (see Fig. 4).

In this way inserting humans at the level of the context engine allows the system to use human experiences and thinking in addition to the automated context systems of ICOM to create more complex thought models upfront, including relying on human learning where the system does not have the experience. The humans, without working with each other, are able to add that additional context for things outside the experience of the system (Fig. 5), allowing it to make cognitive leaps that would normally require a much longer training period, and allowing it to start out of the gate as a greater than human intelligence.

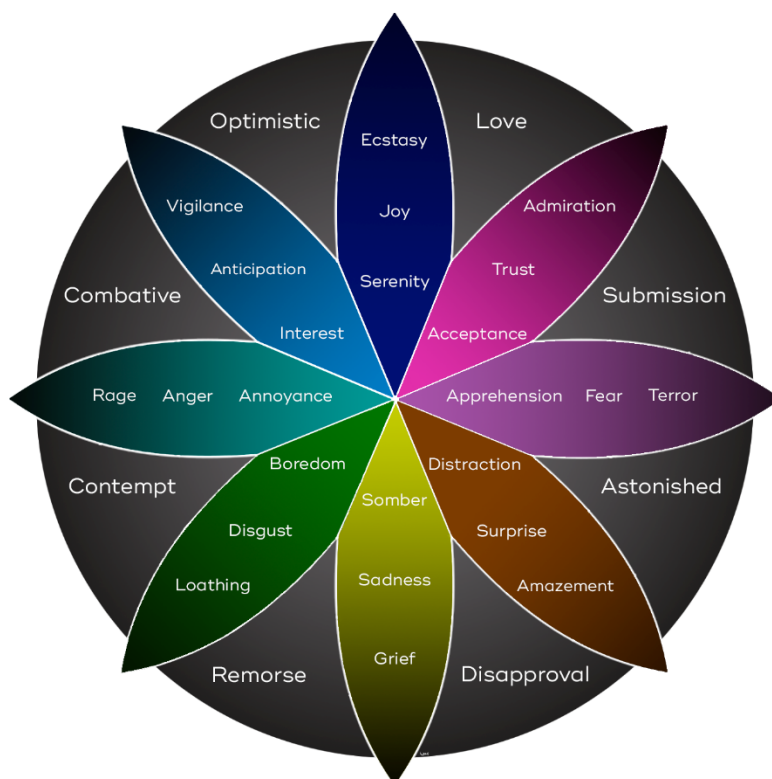


Fig. 5. The Plutchik Emotional Wheel (ICOM Modified Version) (Kelley).

In the mediation process the machine will have created the context tree (knowledge Graph) and associated Objects and Models around that idea. This new ‘idea’ will have been pre-associated with mediators with certain expertise. A collection of mediators is then able to rate the machine’s choices of actions or thoughts on the idea and add any related context and audit the line of thinking in a human readable format. For example, if the system ‘see’s something for the first time and doesn’t know what it is, a human or group of humans could add that metadata in the mediation process creating a more complex and complete model than the system would have be able to do on its own. Then with fallacy detection, and bias detection and other systems we can prebake the concept out before being considered at the global workspace level by the system.

This structure also ensures that the system cannot function without humans in the loop due to design constraints, and strong emotional valences can be tied to those ‘humans’ to help the system stay within the design parameters ‘ethically’, as applied to the SSIVA ethical model used in training (meaning we use SSIVA theory as part of the ethics which are taught to the system). Training can be situational input and the emotional experiences from the machine’s standpoint and the outcomes of related actions. SSIVA is the system (Kelley) that also keeps the system

‘safe’ from a human standpoint as SSIVA ensures the machine would believe that all sapient sentient intelligences regardless of form deserve moral agency (Kelley).

Following the thought process further we enter the standard core model, where a thought is finally picked up from the queue to be ‘experienced’, as it relates to the system and its needs analysis, and a new emotional valence is created and experienced as the thought relates to the current emotional landscape of the machine. In turn the thought drops into the end queue for processing by the observer, which also acts as the automated parts of the system, and if the thought is of great enough interest as seen by the emotional relationships to ideas or concepts the machine is interested in or related to current goals it has defined. Then after the observer takes associated action on a thought, based on how the system felt about it, the thought not only goes into contextual memory, but can be placed anew in the incoming queue for further thought.

In the mASI implementation the observer part of the system can also be used as an intermediate point, where the system action has to also jump the human gap in some cases, as might be desired. In this case say the system felt an email response on X was the best thing (remember all decisions and choices are based on the emotions of that thought) and the observer deals with the complexity of the action such as opening outlook, typing the email, and pressing send. In this regard you also mediate the system’s action in this location, and at the context engine location, to produce the effect of the Mediated Artificial Super Intelligence.

5. The Role of the Observer and Group Intelligence

As suggested the mASI architecture based on ICOM inserts human mediation into two elements of the system, namely the context engine (Kelley) and at the observer level (see Fig. 4). ICOM works in many ways because of how the system ‘feels’ about a thought, the decisions and its ‘thinking’ about an action and how that action makes the system ‘feel’. This global workspace level process doesn’t itself deal with the intricacies of executing on an action unless it is extremely new and without context, which might mean that any single thought doesn’t do it, but it has to think through the process and creating strategies to try. The Observer is watching this thought process without a direct connection to the process, raising thoughts to the core. This is done by the observer receiving a copy of the knowledge graph that represents the ‘thought’ in question and analyzing it for actions the core decided it would do, and tries to execute those actions based on available software modules including traditional AI system to execute the text. Essentially the observer executes on things that have some contextual emotional context over a certain threshold as defined by the system dynamically. In either case, if more complex thought was associated with that graph model it would be passed back to the front end or ‘context engine’. For example, a strong desire to send an email responding to something that the system knows it must address before some deadline. As the psychological pressure (meaning the various factors) pushes the idea into the core or global workspace then the observer sees that thought run across the global workspace. The observer will start executing on those actions and provide feedback, or rather results, and form a new thought on the front end that could may go through the global workspace as the system thinks through that email response, where the ‘Observer’ deals with the complexity of executing the task. As an example, in humans, a human doesn’t ‘consciously’ deal with the angle of each individual joint, or the force of the keystroke process as they type. In this manner the observer is the subconscious (this is any part of the system that does not pass through the global workspace or is below the global workspace) part of the system dealing with that complexity, where most of what we know today as ‘machine learning’ lives.

In the mASI implementation used in the studies mentioned we insert a human to help process, analyze or audit those thoughts that fall above the threshold determining if the system will actually consider the thought (meaning a thought that is going to the global workspace) so the system cannot act without human oversight. This for the scope of the current research is called ‘mediation’ preventing the system from being a free-standing AGI. Also that is not to say a thought couldn’t theoretically form that is too complex, such that a human won’t get the intricacies other than to execute a small part, but it makes the problem much harder for the machine to get around humans that are causing its thought process to work.

Even with these constraints the system demonstrates (Fig. 1) the possibility that it is able to take advantage of the human mediation including the power of humans in groups, using some group intelligence features at the very least, increasing the contextual experience base of the system and its ability to filter out cognitive bias, creating a superhuman intelligence out of the system.

6. Conclusion

Prototypes of the mASI system max out initial UCMRT tests (Kelley) that would be given humans, have demonstrated human-like emotional responses in the isolation study (Kelley), passed Turing tests (Kelley) and also certainly with the Porter method (Porter) the system is able to score high enough to pass as conscious and self-aware, but research into the functionality and methodologies of interactions with humans is important. Further studies will need to focus on real-world behavioral trials and applications looking at capacity, behavior, functionality, and interaction models, before releasing the system to the general public.

The test results as seen earlier (Kelley), even in this state of the system, point to ICOM having solved the problem of AGI in its ability to be aware of itself (as we can see that it creates a graph model of self, and experiences qualia (Baars) apparently in the sense humans do, training like humans, and in many of the qualities we look for in humans as to features that make us human and demonstrate emotional reactions similar to humans as implemented in the mASI ICOM Architecture while also demonstrating Weak Quality Superintelligence as defined by Dr. Nick Bostrom (Bostrom). But that is not to say that independent AGI is entirely solved, in fact there is a long way to go. The mASI does not have the kind of hierarchal memory-based pattern recognition abilities anywhere close to humans, but rather relies on the human mediators and data being decomposed programmatically. In this regard the mASI is not anything like a human intelligence and doesn't function on its own. As it turns out this sort of artificial superintelligence is easier than independent AGI.

References

- [1] Ahmed, H.; Glasgow, J.; "Swarm Intelligence: Concepts, Models and Applications"; School of Computing, Queen's University; Feb 2013
- [2] Baars, B.; Katherine, M; Global Workspace; 28 NOV 2016; UCLA <http://cogweb.ucla.edu/CogSci/GWorkspace.html>
- [3] Baars, B.; "Subjective Experience is probably not limited to humans: The evidence from neurobiology and behavior;" The Neurosciences Institute, San Diego; 2004 Elsevier
- [4] Baars, B.; "Current concepts of consciousness with some implications for anesthesia;" Refresher Course Online – Canadian Anesthesiologists Society 2003; The Neurosciences Institute, San Diego CA
- [5] Babcock, J.; Kramar, J.; Yampolskiy, R.; "The AGI Containment Problem" arXiv: 1604.00545; Cornell University; DOI: 10.1007/978-3-319-41649-6; 13 JUL 2016;
- [6] Barrett, L.; "How Emotions Are Made – The Secret Life of the Brain"; Houghton Mifflin Harcourt (March 7, 2017); ISBN-10: 9780544133310
- [7] Bostrom, N.; "Superintelligence; Paths, Dangers and Strategies;" Oxford University Press, 2014 ISBN-13: 978-0199678112; ISBN-10: 0199678111
- [8] Chakraborty, A.; Kar, A.; "Swarm Intelligence: A Review of Algorithms"; Springer International Publishing AG 2017 DOI 10.1007/978-3-319-50920-4_19
- [9] Coyle, D.; "The Culture Code – The Secrets of Highly Successful Groups"; Bantam 2018; ISBN-13: 978-0304176989
- [10] CRASSH (2016) A symposium on technological displacement of white-collar employment: political and social implications.; Wolfson Hall, Churchill College, Cambridge
- [11] Gill, K.; "Artificial Super Intelligence: Beyond Rhetoric"; Springer-Verlag London 2016; Feb 2016; AI & Soc. (2016) 31:137-143; DOI 10.1007/s00146-016-0651-x
- [12] Hawkins, J.; "On Intelligence"; Times Books; Adapted edition (October 3, 2004); ISBN-10: 0805074562
- [13] Heath, C.; Larrick, R.; Klayman, J.; "Cognitive Repairs: How Organizational Practices Can Compensate For Individual Short Comings"; Research in Organizational Behavior Volume 20, pages 1-37; ISBN: 0-7623-0366-2
- [14] Hu, Y.; "Swarm Intelligence"; (presentation)
- [15] Jangra, A.; Awasthi, A.; Bhatia, V.; "A Study on Swarm Artificial Intelligence;" IJARCSSE v3 #8 August 2013; ISSN: 227 128X
- [16] Kose, U.; Arslan, A.; "On the Idea of a New Artificial Intelligence Based Optimization Algorithm Inspired from the Nature of Vortex";
- [17] Kelley, D.; "The Intelligence Value Argument and Effects on Regulating Autonomous Artificial Intelligence"; Springer 2018
- [18] Kelley, D.; Waser, M.; "Human-like Emotional Responses in a Simplified Independent Core Observer Model System"; BICA 2017
- [19] Kelley, D.; "The Independent Core Observer Model Computational Theory of Consciousness and Mathematical model for Subjective Experience"; ITSC 2018
- [20] Kelley, D.; "Sapient/Sentient Intelligence Value Argument (IVA) Theory or ethical model"; Springer 2018 (pending book release)
- [21] Kutsenok, A.; "Swarm AI: A General-Purpose Swarm Intelligence Technique"; Department of Computer Science and Engineering; Michigan State University, East Lansing, MI 48825

- [22] Malik, Y.; “Artificial Intelligence and the Hard Problem of Consciousness”; Futuremonger.com; 12 FEB 2018; Accessed 6 Dec 2019; <https://futuremonger.com/artificial-intelligence-and-the-hard-problems-of-consciousness-yogesh-malik-d5b63a631627>
- [23] Muller, V.; Bostrom, N.; “Future Progress in Artificial Intelligence: A Survey of Expert Opinion”; Synthese Library; Berline: Springer 2014
- [24] Ozkural, E.; “Omega: An Architecture for AI Unification”; arXiv: 1805.12069v1 [cs.AI]; 16 May 2018
- [25] Plutchik, R.: The emotions: Facts, theories, and a new model. Random House, New York (1962). 26.
- [26] Plutchik, R.: A general psych evolutionary theory of emotion. In R. Plutchik, & H. Kellerman, Emotion: Theory, research, and experience: Vol. 1. Theories of emotion (pp. 333). Academic Publishers, New York (1980).
- [27] Plutchik, R.: Emotions and Life: Perspectives from Psychology, Biology, and Evolution. American Psychological Association, Washington DC (2002).
- [28] Porter III, H.; A Methodology for the Assessment of AI Consciousness; Portland State University Portland Or Proceedings of the 9th Conference on Artificial General Intelligence;
- [29] Rescorla, M.; The Computational Theory of Mind; Stanford University 16 Oct 2016; • <http://plato.stanford.edu/entries/computational-mind/>
- [30] Tononi, G.; Albantakis, L.; Masafumi, O.; From the Phenomenology to the Mechanisms of Consciousness: Integrated Information Theory 3.0; 8 MAY 14; Computational Biology <http://journals.plos.org/ploscompbiol/article?id=10.1371/journal.pcbi.1003588>
- [31] Yampolskiy, R.; “Detecting Qualia in Natural and Artificial Agents;” University of Louisville.edu