Perspectives on the Emerging Field of Autonomous Systems and its Theoretical Foundations

Yingxu Wang[1], *Fellow, IEEE,* Konstantinos N. Plataniotis[2], *Fellow, IEEE,* Arash Mohammadi[3], *SM, IEEE*, Lucio Marcenaro[4], *SM, IEEE*, Amir Asif[5], *SM, IEEE,* Ming Hou[6], *SM, IEEE,* Henry Leung[7], *Fellow, IEEE,* and Marina Gavrilova[8] *SM, IEEE*

[1,7] FIEEEs, Dept. of Electrical & Software Engineering
Schulich School of Engineering and Hotchkiss Brain Institute
Int'l Institute of Cognitive Informatics & Cognitive Computing (I2CICC)
University of Calgary, Canada
Emails: yingxu@ucalgary.ca and leungh@ucalgary.ca

[2] FIEEE, Dept. of Electrical & Computer Engineering
University of Toronto, ON, Canada
Email: kostas@ece.utoronto.ca

[3,5] SMIEEEs, Dept. of Computer Science
Concordia University, Montreal, Canada
Emails: arash.mohammadi@co ncordia.ca and amir.asif@concordia.ca

[4] SMIEEE, Dept. of DITEN, University of Genova, Italy
Email: lucio.marcenaro@unige.it

[6] SMIEEE, Toronto Research Centre, DRDC, Canada
Email: ming.hou@drdc-rddc.gc.ca

[8] SMIEEE, Dept. of Computer Science
University of Calgary, Canada
Emails: mgavrilo@ucalgary.ca

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Abstract — Autonomous systems are advanced intelligent systems and general AI technologies triggered by the transdisciplinary development in intelligence science, system science, brain science, cognitive science, robotics, computational intelligence, and intelligent mathematics. AS are driven by the increasing demands in the modern industries of cognitive computers, deep machine learning, robotics, brain-inspired systems, self-driving cars, internet of things, and intelligent appliances. This paper presents a perspective on the framework of autonomous systems and their theoretical foundations. A wide range of application paradigms of autonomous systems are explored.

Keywords **—** Autonomous systems, intelligence science, system science, intelligent signal processing, general AI theory, brain-inspired systems

I. Introduction

Autonomous systems (AS) are an emerging field of advanced computational intelligence triggered by transdisciplinary developments in intelligence, cognitive, and system sciences as well as intelligent signal processing theories [1-12]. AS enable humans to involve in-the-loop of intelligent systems in order to coherently augment both human and machine intelligence to the maximum. AS lead to a General AI (GAI) theory [7, 20] for advancing machine intelligence.

AS refer to intelligent systems that "exhibit goal-oriented and potentially unpredictable and non-fully deterministic behaviors" by NATO [11]. In basic studies of intelligence science and systems science, the field of AS investigates intelligent systems for implementing advanced human intelligence by computational systems, neural networks, deep machine learning, and Intelligent Mathematics (IM) [14], which embodies high-level machine intelligence built on those of imperative and adaptive systems.

It is recognized that the theoretical foundations for AI in general, and for AS in particular, were not sufficiently mature in the past 60 years for intelligent engineering. As a consequence, few fully autonomous systems have been developed [5, 9, 10, 11]. The state-of-the-art of AI systems is still bounded by the intelligence bottleneck of adaptive systems where machine intelligence is constrained by the low-level reflexive, imperative, and deterministic intelligent abilities [7].

The transdisciplinary advances in intelligence, cognition, computer, signal/sensor, and system sciences have triggered the emerging field of AS [5, 6, 10]. The ultimate goal of AS is to implement a brain-inspired system that may think and act as a human counterpart in hybrid intelligent systems. AS are driven by the increasing demands in the modern industries of cognitive computer, deep machine learning, robotics, brain-inspired systems, self-driving cars, internet of things, and intelligent appliances [6].

This paper explores the nature and the theoretical framework of AS beyond traditional reflexive, imperative, and adaptive systems. A hierarchical intelligence model is introduced in Section II to elaborate the evolution of human and system intelligence as a recursive structure and an inductive process. The theoretical foundations of AS are formally described in Section III by a recursive mathematical model of AS. Then, the framework of IEEE ICAS'21 program is presented in Section IV which represents the co-chairs' perspectives on the inaugural conference series of AS and engineering applications.

II. The Emergence of Autonomous Systems

The transdisciplinary advances towards AS are explored in this section, which seeks what kinds of structural and behavioral

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properties may constitute the intelligence power of AS beyond traditional systems. It explains how system intelligence aggregates from reflexive, imperative, adaptive intelligence to autonomous and cognitive intelligence.

2.1 From Reflexive, Imperative, Adaptive Systems to Autonomous and Cognitive Systems

Intelligence is a paramount cognitive ability of humans that may be mimicked by computational intelligence and AS. *Intelligence science* is a contemporary discipline that studies the mechanisms and properties of intelligence, and the theories of intelligence across the neural, cognitive, functional, and mathematical levels from the bottom up [3, 9, 14, 20]. Therefore, the level of intelligent is a key characteristic for distinguishing if a system is an AS underpinned by intelligence science.

Definition 1. *Intelligence* $\dot{\mathbb{I}}$ is a human, animal, or system ability that autonomously transfers a piece of information I into a behavior B (to-do) or an item of knowledge K (to-be), particularly the former:

$$\begin{aligned} \dot{\mathbb{I}} &= f_{to-do} : I \rightarrow B \\ &\mid\ f_{to-be} : I \rightarrow K \end{aligned} \quad (1)$$

A classification of intelligent systems may be derived based on the forms of inputs and outputs dealt by the system as shown in Table 1. The reflexive or imperative systems are capable to process deterministic stimuli by deterministic or indeterministic algorithms, respectively. The adaptive systems are designed for dealing with indeterministic stimuli by deterministic behaviors predefined at design time. However, AS are characterized by both indeterministic stimuli and indeterministic (problem-specific or goal-oriented) behaviors pending for run-time contexts.

Table 1. Characteristics of autonomous and nonautonomous systems

Intelligent behaviors		Behavior (O)	
		Deterministic	Indeterministic
Stimulus (I)	Deterministic	*Reflexive system*	*Imperative system*
	Indeterministic	*Adaptive system*	*Autonomous system*

Definition 2. *Autonomous systems* (*AS*) are advanced intelligent systems that function without human intervention for implementing complex cognitive abilities aggregating from reflexive, imperative, and adaptive intelligence to autonomous and cognitive intelligence.

AS is an indeterministic nonlinear system that depends not only on current stimuli or demands, but also on internal status, willingness, and knowledge formed by long-term historical events and current rational or emotional goals. AS implements nondeterministic, context-dependent, and adaptive behaviors closer to the level of human cognitive intelligence.

2.2 The Hierarchical Model of Intelligence for AS

A *Hierarchical Intelligence Model* (HIM) is introduced to classify the levels of intelligence and their recursive properties in intelligence science as illustrated in Figure 1 based on the *abstract intelligence* (αI) theory [20]. As shown in Figure 1, the levels of natural and system intelligence may be aggregated from those of reflexive, imperative, adaptive, autonomous, and cognitive intelligence with 16 categories of intelligent behaviors. Types of system intelligence across the HIM layers are explained in the following subsections using the *event-dispatching mechanism* [18] as defined in Eq. (2). Rigorous mathematical models will be formally described in Section III.

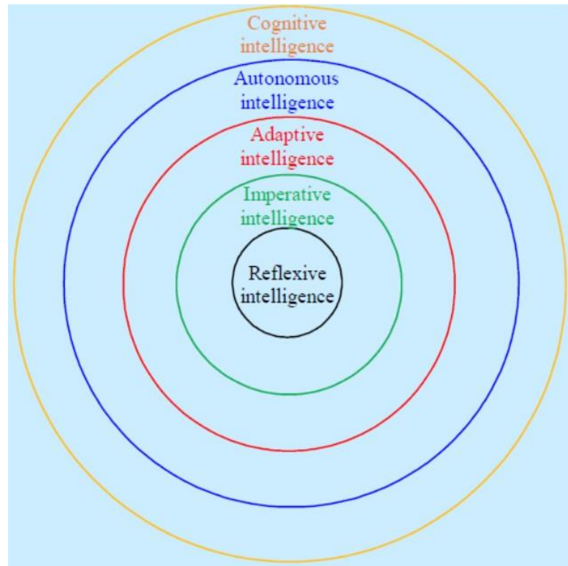

Fig. 1. The Hierarchical Intelligence Model (HIM)

1) *Reflexive intelligence* $\dot{\mathbb{I}}_{ref}$ is the bottom-layer intelligence of AS coupled by a stimulus and a reaction. $\dot{\mathbb{I}}_{ref}$ is shared among humans, animals, and machines, which forms the foundation of higher layer intelligence. $\dot{\mathbb{I}}_{ref}$ is a set of wired behaviors directly driven by specifically coupled external stimuli or trigger events.

2) *Imperative intelligence* $\dot{\mathbb{I}}_{imp}$ is a form of instructive and reflective behaviors dispatched by a system based on the layer of reflexive intelligence. $\dot{\mathbb{I}}_{imp}$ encompasses event-driven behaviors, time-driven behaviors, and interrupt-driven behaviors. The imperative system powered by $\dot{\mathbb{I}}_{imp}$ is not adaptive yet, and may merely implement deterministic, context-free, and stored-program controlled behaviors as a classical stored-program-controlled system.

3) *Adaptive intelligence* $\dot{\mathbb{I}}_{adp}$ is a form of run-time determined behaviors where a set of predictable scenarios is determined for processing variable problems. $\dot{\mathbb{I}}_{adp}$ encompasses analogy-based behaviors, feedback-modulated behaviors, and environment-awareness behaviors. $\dot{\mathbb{I}}_{ada}$ is constrained by deterministic rules where the scenarios are prespecified in design-time. If a request is out of the defined domain of an adaptive system, its behaviors will no longer be adaptive or predictable.

4) *Autonomous intelligence* $\dot{I}_{aut}$ is the 4th-layer intelligence powered by internally motivated and self-generated behaviors underpinned by senses of system consciousness and environment awareness. $\dot{I}_{aut}$ encompasses the perceptive behaviors, problem-driven behaviors, goal-oriented behaviors, decision-driven behaviors, and deductive behaviors built on Layers 1 through 3 intelligent behaviors. $\dot{I}_{aut}$ is self-driven by the system based on internal consciousness and environmental awareness beyond the deterministic behaviors of adaptive intelligence. $\dot{I}_{aut}$ represents nondeterministic, context-dependent, run-time autonomic, and self-adaptive behaviors.

5) *Cognitive intelligence* $\dot{I}_{cog}$ is the 5th-layer of intelligence that generates inductive- and inference-based behaviors powered by autonomous reasoning. $\dot{I}_{cog}$ encompasses the knowledge-based behaviors, learning-driven behaviors, inference-driven behaviors, and inductive behaviors built on the intelligence powers of Layers 1 through 4. $\dot{I}_{cog}$ is nonlinear, nondeterministic, context-dependent, knowledge-dependent, and self-constitute, which represents the highest level of system intelligence mimicking the brain.

The mathematical models of HIM explain why the current level of machine intelligence had been stuck at the level of adaptive intelligence in the past 60 years, because of the lack of matured theories and mathematical means for implementing fully autonomous and cognitive intelligence comparable to human natural intelligence.

III. The Theoretical Foundations of Autonomous Systems

The framework of AS in Section II reveals that *autonomy* is a property of intelligent and cognitive systems that may change their behaviors in response to unanticipated events and unclear causality without human intervention driven by autonomous decision-making beyond predetermined adaptive behaviors. AS implements nondeterministic, context-dependent, and self-adaptive behaviors dependent not only on current stimuli or demands, but also on internal status and willingness formed by long-term historical events and current rational or emotional goals. The major capabilities of AS will need to be extended to the cognitive intelligence level towards highly intelligent systems beyond classic adaptive and imperative systems.

On the basis of the HIM model, a set of generic mathematical models of AS may be introduced as a rigorous theory towards designed and implementation of various AS paradigms.

Definition 3. The *mathematical model of AS* is a high-level intelligent system for implementing advanced intelligent abilities compatible to human intelligence in systems as an *event* ($e|\mathrm{S}$) - *behavior* ($B|\mathrm{PM}$) dispatching mechanism $@e|\mathrm{S} \hookrightarrow B|\mathrm{PM}$:

$$AS \triangleq \underset{i=1}{\overset{n_{AS}}{R}} @e^{i}_{AS}|\mathrm{S} \hookrightarrow [B_{AS}(i)|\mathrm{PM} \mid B_{AS}(i)|\mathrm{PM} \geq 4] \qquad (2)$$

which extends the power of system intelligence from reflexive, imperative, and adaptive to autonomous and cognitive intelligence, where the *big-R* calculus denotes recurrent structures or iterative behaviors [22].

The Mathematical Model of Hierarchical AS Intelligence

LevelsOfIntelligence|SM $\triangleq$

{**1. Reflexive intelligence** (wired behaviors)

1.1 $\dot{I}_{ref} \triangleq \underset{i=1}{\overset{n_{ref}}{R}} @e_i|\mathrm{REF} \hookrightarrow B_{ref}(i)|\mathrm{PM}$ // Sensory-driven intelligence

2. Imperative intelligence (predefined event-driven behaviors)

2.1 $\dot{I}^{e}_{imp} \triangleq \underset{i=1}{\overset{n_{e}}{R}} @e_i|\mathrm{E} \hookrightarrow B^{e}_{imp}(i)|\mathrm{PM}$ // Event-driven intelligence

2.2 $\dot{I}^{t}_{imp} \triangleq \underset{i=1}{\overset{n_{t}}{R}} @e_i|\mathrm{TM} \hookrightarrow B^{t}_{imp}(i)|\mathrm{PM}$ // Time-driven intelligence

2.3 $\dot{I}^{int}_{imp} \triangleq \underset{i=1}{\overset{n_{int}}{R}} @e_i|\odot \hookrightarrow B^{int}_{imp}(i)|\mathrm{PM}$ // Interrupt-driven intelligence

3. Adaptive intelligence (run-time determined behaviors)

3.1 $\dot{I}^{ab}_{adp} \triangleq \underset{i=1}{\overset{n_{ab}}{R}} @e_i|\mathrm{AR} \hookrightarrow B^{ab}_{adp}(i)|\mathrm{PM}$ // Analogy-based intelligence

3.2 $\dot{I}^{fm}_{adp} \triangleq \underset{i=1}{\overset{n_{fm}}{R}} @e_i|\mathrm{FM} \hookrightarrow B^{fm}_{adp}(i)|\mathrm{PM}$ // Feedback-modulated intel.

3.3 $\dot{I}^{ea}_{adp} \triangleq \underset{i=1}{\overset{n_{ea}}{R}} @e_i|\mathrm{EA} \hookrightarrow B^{ea}_{adp}(i)|\mathrm{PM}$ // Environment-aware intel.

4. Autonomous intelligence (self-driven behaviors)

4.1 $\dot{I}^{pe}_{aut} \triangleq \underset{i=1}{\overset{n_{pe}}{R}} @e_i|\mathrm{PE} \hookrightarrow B^{pe}_{aut}(i)|\mathrm{PM}$ // Perceptive intelligence

4.2 $\dot{I}^{pd}_{aut} \triangleq \underset{i=1}{\overset{n_{pd}}{R}} @e_i|\mathrm{PD} \hookrightarrow B^{pd}_{aut}(i)|\mathrm{PM}$ // Problem-driven intelligence

4.3 $\dot{I}^{go}_{aut} \triangleq \underset{i=1}{\overset{n_{go}}{R}} @e_i|\mathrm{GO} \hookrightarrow B^{go}_{aut}(i)|\mathrm{PM}$ // Goal-driven intelligence

4.4 $\dot{I}^{dd}_{aut} \triangleq \underset{i=1}{\overset{n_{dd}}{R}} @e_i|\mathrm{DD} \hookrightarrow B^{dd}_{aut}(i)|\mathrm{PM}$ // Decision-driven intel.

4.5 $\dot{I}^{de}_{aut} \triangleq \underset{i=1}{\overset{n_{de}}{R}} @e_i|\mathrm{DE} \hookrightarrow B^{de}_{aut}(i)|\mathrm{PM}$ // Deductive intelligence

5. Cognitive intelligence (learning and inference-based behaviors)

5.1 $\dot{I}^{kb}_{cog} \triangleq \underset{i=1}{\overset{n_{kb}}{R}} @e_i|\mathrm{KB} \hookrightarrow B^{kb}_{cog}(i)|\mathrm{PM}$ // Knowledge-based intel.

5.2 $\dot{I}^{ld}_{cog} \triangleq \underset{i=1}{\overset{n_{ld}}{R}} @e_i|\mathrm{LD} \hookrightarrow B^{ld}_{cog}(i)|\mathrm{PM}$ // Learning-driven intel.

5.3 $\dot{I}^{if}_{cog} \triangleq \underset{i=1}{\overset{n_{if}}{R}} @e_i|\mathrm{IF} \hookrightarrow B^{if}_{cog}(i)|\mathrm{PM}$ // Inference-driven intel.

5.4 $\dot{I}^{id}_{cog} \triangleq \underset{i=1}{\overset{n_{id}}{R}} @e_i|\mathrm{ID} \hookrightarrow B^{id}_{cog}(i)|\mathrm{PM}$ // Inductive intelligence

}

Fig. 2. The mathematical framework of hierarchical AS intelligence

According to the HIM model, the *behavioral model* of AS is inclusively aggregated from the bottom up among $AS|\S \triangleq (B_{Ref}, B_{Imp}, B_{Adp}, B_{Aut}, B_{Cog})$, where $|\S$ denotes a system embodied by the set of reflexive, imperative, adaptive, autonomous, and cognitive behaviors as shown in Figure 2.

Theorem 1. An *AS* is characterized by a) a *recursively hierarchical* architecture and b) a series of *recursively inclusive* behaviors:

$$AS|\S \triangleq \begin{cases} a)\ \mathop{R}\limits_{k=1}^{4} B^k(B^{k-1}), B^0 = \mathop{R}\limits_{i=1}^{n_{ref}} @e_i|\mathrm{REF} \hookrightarrow B_{ref}(i)|\mathrm{PM} \\ b)\ B_{Cog} \supseteq B_{Aut} \supseteq B_{Ada} \supseteq B_{Imp} \supseteq B_{Ref} \end{cases} \quad (3)$$

Proof. $\forall AS|\S$, a) The recursive behavioral architecture $\mathop{R}\limits_{k=1}^{4} B^k(B^{k-1})$ is necessary to aggregate the *AS*' functions through B^0 to B^4 from the bottom up, *iff* B^0 is deterministic; b) Because the five-level behaviors are in a partial order, the *recursive inclusivity* across all layers of behaviors is sufficient for composing the AS.

■

Theorem 1 indicates that any lower layer behavior of AS is a subset of those of a higher layer. In other words, any higher layer behavior of AS is a natural aggregation of those of lower layers as shown in Figure 2. According to the necessary and sufficient conditions stated in Theorem 1, a hybrid AS with humans in the loop will gain strengths towards the implementation of cognitive intelligent systems. The cognitive AS will sufficiently enable a powerful GAI system with the strengths of both human and machine intelligence. This is what intelligence and system sciences may inspire towards the development of fully autonomous systems in highly demanded engineering applications.

The HIM model and Theorem 1 reveal the ultimate goal of AI and machine intelligence. They lead to the finding of the 6^{th} and most important form of machine learning known as *cognitive knowledge learning* [17] beyond traditional learning technologies for object identification, cluster classification, pattern recognition, functional regression and behavior generation (gaming) [19]. They also enabled the discovery that the basic unit of knowledge is a *binary relation* (*bir*) [17].

IV. The Framework of IEEE ICAS'21

The framework of the inaugural IEEE International Conference on Autonomous Systems (ICAS'21) is highlighted in Table 2 where three themes are covered in the categories of theoretical foundations of AS, emerging fields of AS, and engineering paradigms.

Advances in *AS* are expected to pave a way towards highly intelligent machines for augmenting human capabilities. Typical emerging *AS* include unsupervised computational intelligence, cognitive systems, brain-inspired systems, general automobiles, unmanned systems, human intelligence augmentation systems, intelligent defence systems, and intelligent IoTs.

Table 2. The Program Framework of IEEE ICAS'21

Theoretical Foundations of AS	Emerging Fields of AS	AS Engineering
• Intelligent foundations of AS	• Autonomous computers	• Applied paradigms of AS
• System foundations of AS	• Autonomous algorithms	• Autonomous programming
• Mathematical foundations of AS	• Brain-inspired AS	• Cognitive inference Engines
• Computational foundations of AS	• Autonomous machine learning	• Autonomous robots
• Brain science foundations of AS	• Autonomous IoTs	• Distributed AS
• Cognitive foundation of AS	• Self-driving vehicles and vessels	• Embedded AS
• Bottlenecks of adaptive Systems	• Autonomous robots	• Communications among AS
• Indeterministic and uncertainty behaviors of AS	• Real-time AS	• Communications Between AS and humans
• Interaction between humans and AS	• Autonomous unmanned systems	• Autonomous operating Systems
• Autonomous Computing platforms	• Trustworthiness of AS	• Autonomous sensors
• Neurological foundations of AS	• Mission critical systems	• Autonomous swarms
• Signal processing theories of AS	• Autonomous perception/awareness	• Social AS

None of the *AS* applications is trivial towards the next generation of cognitive computers, *GAI*, and hybrid symbiotic human-machine societies. Recent *AS* projects undertaken in our labs address challenges for abstract intelligence, intelligent mathematics for *AS*, the tripartite framework of *AS* trustworthiness, autonomous decision making, a transdisciplinary theory for cognitive cybernetics, humanity, and systems science, cognitive foundations of knowledge science, and the abstract intelligence theory for *AS* [1, 20-26]. The advances of *AS* theories and technologies will lead to the era of intelligence revolution for unprecedented breakthroughs to enable pervasive AS, which help to augment human intelligent power by autonomous and cognitive intelligence.

V. Conclusion

It has been recognized that autonomous systems are emerged from perceptive, problem-driven, goal-driven, decision-driven, and deductive intelligence. This work has explored basic research on the intelligence and system foundations of autonomous systems. A Hierarchical Intelligence Model (HIM) has been developed for elaborating the properties of autonomous systems built upon reflexive, imperative, and adaptive systems. The nature of system autonomy and human in-the-loop of autonomous systems has been formally analyzed. This work has provided a theoretical framework for developing cognitive autonomous systems towards highly demanded engineering applications including brain-inspired cognitive systems, unmanned systems, self-driving vehicles, cognitive robots, and intelligent IoTs.

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