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Understanding the Evolution and Applications of Intelligent Systems via a Tri-X Intelligence (TI) Model

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Abstract: The evolution and application of intelligence have been discussed from perspectives of life, control theory and artificial intelligence. However, there has been no consensus on understanding the evolution of intelligence. In this study, we propose a Tri-X Intelligence (TI) model, aimed at providing a comprehensive perspective to understand complex intelligence and the implementation of intelligent systems. In this work, the essence and evolution of intelligent systems (or system intelligentization) are analyzed and discussed from multiple perspectives and at different stages (Type I, Type II and Type III), based on a Tri-X Intelligence model. Elemental intelligence based on scientific effects (e.g., conscious humans, cyber entities and physical objects) is at the primitive level of intelligence (Type I). Integrated intelligence formed by two-element integration (e.g., human-cyber systems and cyber-physical systems) is at the normal level of intelligence (Type II). Complex intelligence formed by ternary-interaction (e.g., a human-cyber-physical system) is at the dynamic level of intelligence (Type III). Representative cases are analyzed to deepen the understanding of intelligent systems and their future implementation, such as in intelligent manufacturing. This work provides a systematic scheme, and technical supports, to understand and develop intelligent systems.

Keywords: Tri-X Intelligence; cyber-physical systems; human-cyber systems; intelligent systems; intelligent manufacturing



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1. Introduction

In recent decades, intelligence has been a hot topic in various areas including human science, biology, computer and information science and social science [1]. Intelligence is well defined for its capabilities of perception and cognition, as well as its wide application of all living systems to natural laws [2–4]. This broad definition maximizes coverage of a variety of intelligent phenomena. The common definition of intelligence is to realize and maximize the value of the function of artificial systems according to human desires by natural laws, to be activated upon a human's request. Intelligence represents the system's responsiveness to environmental changes through an autonomous decision-making process, which enables the system to react using proper actions at the proper time in the proper way to achieve the objectives. Norbert Wiener published his book "Cybernetics: control and communication in the animal and the machine" in 1948 [5]. Wiener tried to analyze the difference between humans and machines. He stated that the special abilities of humans are in recognizing and adapting to the environment changes. In his opinion, artificial systems and living systems share a similar logic, in which the human is a control and communication system as is a machine. In his book, "cybernetics" is a concept with special

meaning, including control, feedback, communication and interaction. It is a process followed by a series of procedures, including constant acquisition of condition changes, reaction, and continuous optimization. It is an autonomous process that an intelligent entity adapts to by control algorithms, unifying recognition, decision, and feedback to handle environmental uncertainties. The word “cyber” is closely related to cybernetics; automatic control systems in both machines and living things. Compared to human intelligence, the characteristics of machine intelligence can be interpreted as data circulation rather than human movement, machine computing rather than human brainpower, automated machining rather than manual operation. Driven by complex business processes, limited time windows and surge labor costs, the value of the above three characteristics is increased by an order of magnitude [6]. For example, the concept of intelligent manufacturing was proposed to liberate humans from tasks that can be done by machines. Much evidence indicates that machines can perform better in certain tasks compared to humans [4,7].

The level of system intelligence is measured by the ability for decision-making. For example, a higher level indicates more situations that a system can handle. Five basic features, including state recognition, real-time analysis, autonomous decision-making, accurate execution and promotion through learning, indicate the level of system intelligence [8]. As an extension of Wiener’s idea, we designed five features to measure the intelligence of a physical entity, a consciousness of humans, and a cyber entity for determining their intelligence levels. According to the five features, Hu et.al [8] classified the intelligent systems into three levels including primitive level (Type I), normal level (Type II), and dynamic level (Type III), as shown in Figure 1. A system with state recognition, real-time analysis, and accurate execution is classified as a primitive-intelligent system. An advanced intelligent system has additional features regarding autonomous decision-making. A system with all five features is an open-intelligent system, also known as a system with a complete level of intelligence.

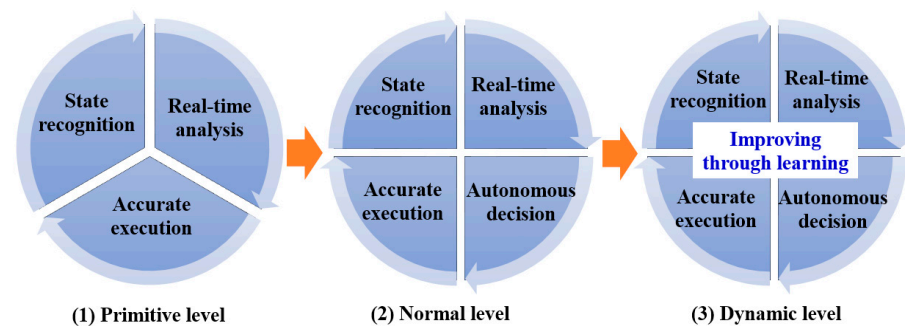


Figure 1. Three levels of intelligence in intelligent systems.

Intelligence has been discussed from the perspectives of life, control theory, artificial intelligence and industrial applications [1,5,9–11]. In dynamic systems, humans may not perform as well as robots in repeated tasks, but they are able to adapt to change, and can often invent out-of-the-box solutions. However, there is no consensus on the evolution of intelligence with the incorporation of human intelligence and its importance. Even though the human’s role and full integration in these systems is often overlooked, the human is an indispensable component in the intelligent systems, especially for supervising and enforcing the intelligence of machines. To address this research gap, the Tri-X Intelligence (TI) model is proposed to systematically analyze the intelligence of humans, the physical world, the cyber world and their interactions. The proposed model consists of three intelligent elements: conscious humans, physical objects and cyber entities (Figure 2). In Figure 2, physical objects include natural substances and artificial systems based on physical materials. Conscious humans can be defined as biological systems with brainpower and awareness. A Cyber system is an advanced digital logic system in a computer with network facilities to drive the software and hardware.

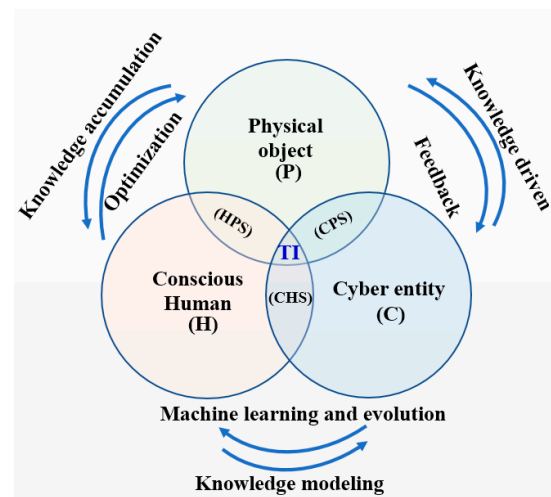


Figure 2. The Tri-X Intelligence (TI) model.

The goal and application area of this work focus on the industrial field including intelligent manufacturing, intelligent energy and intelligent transportation. The rest of the paper is organized as follows. In Sections 2–4, elemental intelligence, integrated intelligence and complex intelligence are discussed based on the hierarchy provided by an HCPS (human–cyber–physical systems) model. In Section 5, representative examples of HCPS are presented in detail. In Section 6, we conclude this work and summarize future research directions.

2. Elemental Intelligence Based on Scientific Effects

2.1. Physical Object

A physical object is one of the original intelligent systems or the zero-generation of intelligent systems. Taking the natural ecosystem as examples, a rock, tree, mountain, water, and even the planet, can recognize outside information, exchange materials/energy, and operate according to natural laws through scientific phenomenon or effect. Intelligence of a physical object can be shown in a scientific manner through geometry, physics, chemistry or biology. The interaction results from different materials following natural laws. The intelligence of a physical object is consistent with primitive intelligence, as shown in Figure 3. An old example of physical intelligence is the steam engine invented in the first industrial revolution [12].

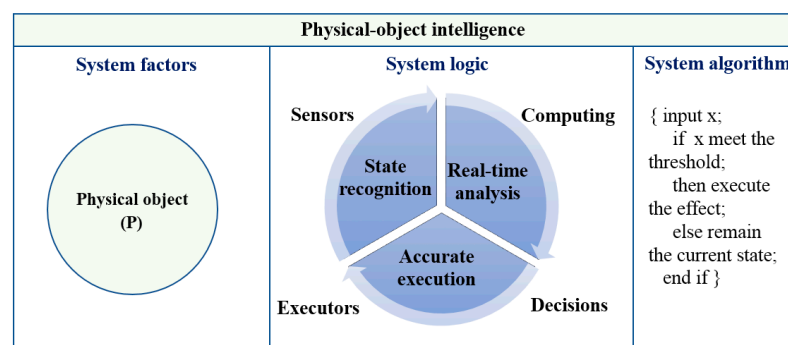


Figure 3. Physical object intelligence (Type I).

In recent years, the advancement of physical object intelligence in the form of intelligent/smart materials has drawn increasing attention. For example, intelligent fibers can recognize changes in the outside environment and inner states and respond to them in a certain manner [13]. Intelligent skin is made of super-thin (nanometer) film polyimide and monocrystalline silicon, which is equipped with tactile sensors to detect changes in temper-

ature, humidity, pressure and transformation [14]. These intelligent materials are produced following interdisciplinary physical laws. Interactions among physical entities are very common in the industry. A variety of physical objects constitute many manufacturing facilities and products, which realize their functions via physical object intelligence. The intelligence of physical objects is often constant over time and relies on other intelligence for continuous improvement and dynamic innovation.

2.2. Conscious Humans

The living intelligence of human is attained from the continuous recognition of nature. It is a type of inherent intelligence developed during evolution. Conscious humans recognize outside information using sense organs and react to outside stimulation through subconscious actions, unconscious actions, or conscious actions that are recognized and controlled by the brain, as shown in Figure 4. For example, humans react immediately when touching extra-hot, frozen, or sharp objects. More importantly, humans learn how to make decisions based on past experiences [15]. Interactions among humans are common in society and determine the basic contents of human lives. Interactions and cooperation among humans create groups, domains and relationships. More importantly, emotional intelligence, also known as emotional quotient (EQ), is the ability of humans to recognize their own emotions and those of others, to discern between different feelings. and to label them appropriately. Emotional information helps to guide thinking and behavior and to manage emotions in order to adapt to various environments or achieve goals [16]. However, there are many known and well-documented human cognitive biases that plague human intelligence and the ability to reason consistently, to make decisions based on evidence, and to make accurate predictions of the future [16]. Other disadvantages of human labor include behavioral differences, forgetting information, mistakes and errors [17].

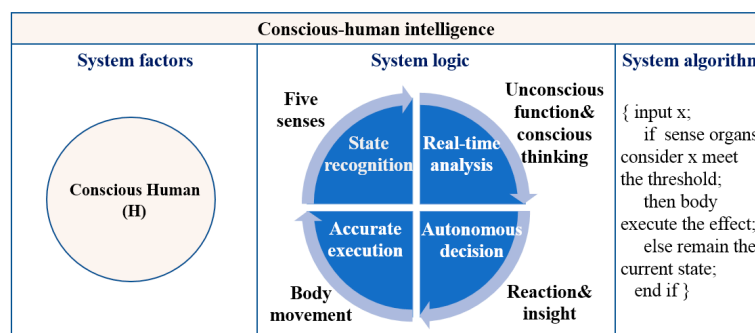


Figure 4. Human intelligence (Type I).

2.3. Cyber Entity

A cyber entity consists of software, hardware and a network that enables digital intelligence or computation intelligence on machines, as shown in Figure 5. For example, computers take inputs through the keyboard, mouse and camera. Autonomous decisions are enabled by the processor unit which is designed to analyze the signal, voice and image in real-time. Computers can execute commands following exact rules, including data storage, image capture and camera angle adaption. Initially, the computer was used for simple calculation and data storage. In the intelligent age, computers have become smarter with the capacity for communication, self-learning and super-computing. Moreover, knowledge systems can be obtained from collaborative learning from interactions among cyber entities [18–20]. However, cyber-entity intelligence (or called machine intelligence) has no setting for creativity, playfulness, fun or curiosity, which are the source of many inventions and breakthroughs [15].

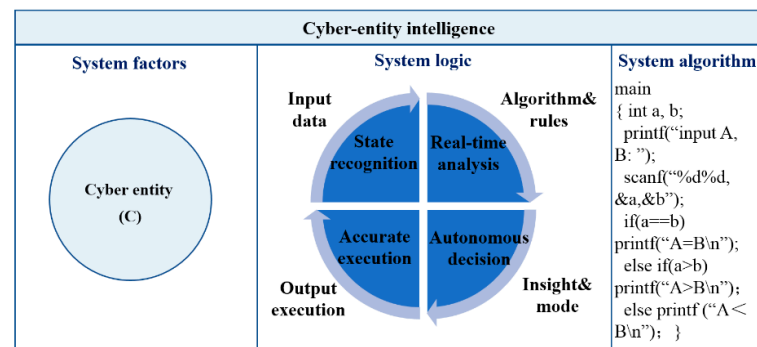


Figure 5. Cyber entity intelligence (Type I).

Today, physical object intelligence commonly exists in areas including new materials, super materials and intelligent materials. Cyber entity intelligence benefits from the development of algorithms and computation capacity. Artificial intelligence with learning ability is growing rapidly and is becoming comparable to human intelligence [21–26]. In summary, due to their own advantages and shortcomings, physical entity intelligence, conscious human intelligence and cyber entity intelligence should be integrated and synergetic in high-level intelligent systems. We seek to confirm that machine intelligence can interact and fuse with other types of intelligence, leading to a more advanced and complex intelligence.

3. Integrated Intelligence Formed by Two-Elements Integration

3.1. Human-Physical System (HPS) Intelligence

Humans can not only design physical objects through physical and mental work but can also generate knowledge in this process. Meanwhile, humans can use the acquired knowledge to create new physical products. In other words, development history is a process of recognizing, exploiting and changing physical objects, as shown in Figure 6. For example, colored pottery encompasses knowledge from hundreds of years ago. The knowledge in the brain and the product is implicit, which is different from explicit knowledge, such as an image or text. Benefiting from the development of explicit knowledge, the physical machine has become increasingly advanced to replace parts aspects of human labor. However, the development of implicit and explicit knowledge HPS is limited due to the restriction of knowledge carriers. The interaction mode with HPS is the typical mode of “human in the loop”. Human and physical machines are the main system elements that keep improving HPS during evolution.

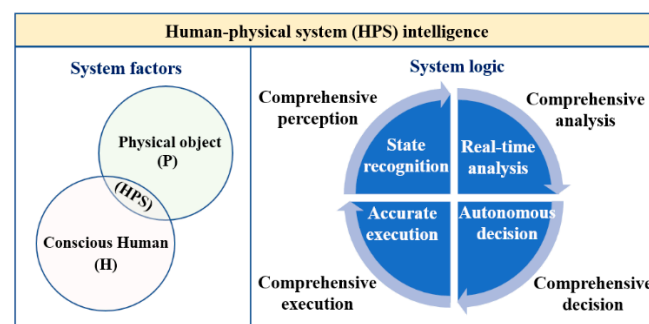


Figure 6. HPS intelligence (Type II).

3.2. Human-Cyber System (HCS) Intelligence

One goal of developing intelligent systems is to increase the interaction of efficiency between humans and cyber systems (e.g., computers) in the form of human-cyber systems (HCS). There are various interaction methods in HCS, such as programmable software [27], brain-computer interfaces [28], and inserted chips [29] between human and cyber systems. Software is a method to transform human intelligence into machine intelligence. Explicit

knowledge is the main source of machine intelligence. The software intermediary interprets the humans' implicit knowledge into explicit knowledge to equip the cyber entity with reasoning ability. The brain-computer interface is a method that extracts brain awareness to control the physical entity via a cyber system. Related technologies have been investigated including communications from brain to machine, from machine to brain, and from brain to brain. An inserted chip is an intrusive connection method. In the future, with the development of super chips, it is possible to realize an interbrain network through inserted super chips. Action recognition is an indirect method to obtain human awareness through various sensors. The language, facial expression, gestures and other information of human awareness can be converted into digital information in cyber entity systems [30]. Taking WeChat as an example [31], recognition and software intermediary tools have been designed to convert screen touch actions into texts to be sent to people via cyber technologies. Interactions between humans and cyber entities to realize HCS intelligence are shown in Figure 7. Although many scientists have focused on brain science, the thinking mechanism of the mind is still unclear [32]. Interactions between human awareness and cyber entities still involve interpreting implicit knowledge to explicit knowledge in order to strengthen digital intelligence. This is a process to convert human intelligence to machine intelligence for more powerful knowledge-based tools.

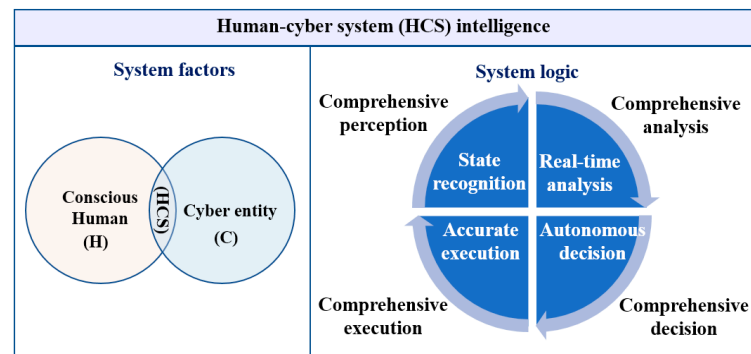


Figure 7. HCS intelligence (Type II).

3.3. Cyber-Physical System (CPS) Intelligence

Interactions between physical objects and cyber entities result in a cyber-physical system (CPS), which is a milestone to promote the development of intelligent systems. CPS was proposed by Helen Gill [33,34] and was introduced into industry by Germany to support Industry 4.0 initiatives [35]. CPS models not only the interaction between physical objects and cyber entities but also a scheme that converts human intelligence to machine intelligence in artificial systems. However, the influence of human intelligence will never disappear and keeps influencing the artificial systems via software and knowledge engines, as shown in Figure 8.

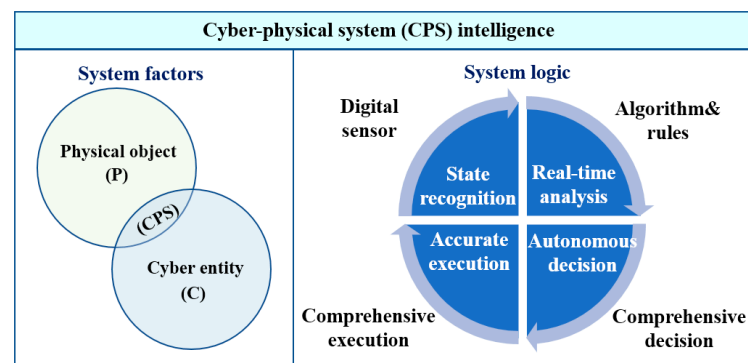


Figure 8. CPS intelligence (Type II).

For instance, CPS is the core technology of smart manufacturing (or intelligent manufacturing) [36]. The reference framework (RAMI 4.0) of CPS proposed by Germany Industry 4.0 consists of a physical layer, integration layer, communication layer, information layer and a function layer, in which the core is the digital technology and network technology [37]. RAMI 4.0 elaborates the concept of an administration shell that is an intermediate software platform including a communication layer, information layer and a function layer. The administration shell is a cyber system to support CPS, which can be applied to a physical object to constitute a CPS. Software is the crucial carrier of a cyber system, which defines new rules and stores knowledge within the restriction of hardware. Human intelligence and artificial intelligence define the majority of reasoning and judging rules in software. The information of physical entities flows into the digital space to create the cyber system. In turn, the cyber system participates in the activities of physical objects through software, which is called the digital twin [38,39]. In the future, more and more physical objects will fuse with digital entities, and more and more digital entities will be adopted to test and control physical objects.

4. Complex Intelligence Formed by Ternary-Interaction

Interactions within physical objects, conscious humans and cyber entities cocreate complex intelligent systems, called the intelligence of system-of-systems (SoS). The different focuses of the components create different applications, as shown in Figure 9. Most of the scenarios in Industry 3.0 and 4.0 have resulted from the fusion of physical objects, conscious humans and cyber entities, in design, production and service [40].

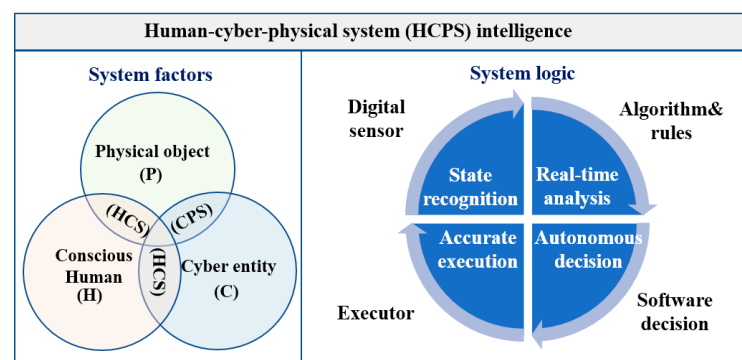


Figure 9. HCPS intelligence (Type III).

An advanced case of ternary-fusion HCPS intelligence is the self-driving automobile [41]. In practice, there are many self-driving automobiles that can handle most of the situations under supervision. Moreover, the 100% self-driving automobile has already been developed at the lab level. Here, AI takes over the driving position of the human operator and operates the self-driving system based on data analytics of the environment and human behavior. This type of intelligent system can not only practice the intelligent circle including recognition, analysis, decision, execution, but is also equipped with learning ability. Human-machine hybrid intelligence is an advanced form of human-machine intelligence. A typical case is Alpha AI software developed by Psibernetix, which can beat American pilots in simulation environments [42]. The chance of making mistakes will increase when a pilot is in control of a supersonic aircraft at 12,000 m and a speed of over 1200 km per hour. However, Alpha AI can increase error tolerance through tactical plan optimization in a dynamic environment. The responsiveness of Alpha AI is 250 times faster than that of a pilot. Alpha AI can be controlled by language commands. The most significant aspect of Alpha AI is that it can learn from other Alpha AI data installed in different places and in different versions to enhance its own performance. Another example is human-robot collaboration [43]. Human-robot collaboration can release human workers from heavy tasks if effective communication channels between humans and robots are established [44]. With the help of sensor technologies, gesture identification, gesture

tracking and gesture classification, human-robot collaboration allows human workers and robots to work together in a shared manufacturing environment.

In summary, the single entity (conscious human, physical object or cyber entity) shows primitive intelligence (Type I) at the unit level. A two-entity integrated system may create normal-level intelligence (Type II) at a system level. Three-entity fusion can generate dynamic-level intelligence (Type III) at the SoS level. Therefore, when considering development from primitive intelligence, intelligentization has evolved over more than 200 years. The development of intelligence will be accelerated in the future resulting in hybrid intelligence and swarm intelligence.

5. Implementation and Applications of Intelligent Systems

Physical systems with primitive intelligence are the oldest intelligent systems; however, their control is limited [6] and the corresponding technologies are easy to generalize. In the Wiener era [5], electricity was adopted for sensing information and driving motors and machinery, which broke through the obstacle between information and the physical entity to increase technology commonality. Due to technology limitations, only simple objects described by differential equations could be controlled in that era. With the development of computational technologies, digital/cyber intelligence has been applied to control more complex objects. In the following section, the implementation and applications of intelligent artificial systems are analyzed based on the evolution and development of system elements.

An artificial system is a set of elements with interaction and interconnection to realize specific functions in the forms of machine, product, workpiece and plants. Its components can be described as four basic subsystems, as shown in Figure 10: power unit, control unit, transmission unit and actuator unit. The executive device (actuator unit) is used for executing actions, the power device for producing and converting energy, the transmission device for transmitting energy and the control device for adjusting the operating parameters of subsystems to allow executive devices to react accurately. In the past decades, industrial evolution occurred with technological developments in artificial systems. The emergence of new machines, new tools and facilities created continuously improving productivity. The four basic components are also evolving constantly. For example, the executive device is updated by introducing new structures and new materials (e.g., intelligent fiber and super materials).

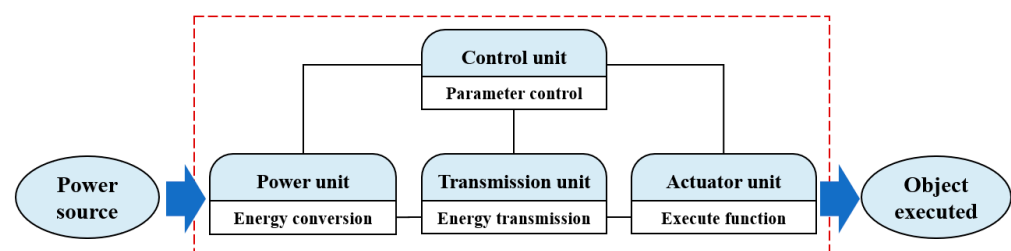


Figure 10. Four basic subsystems of artificial systems.

In recent decades, the control unit in artificial systems has evolved fastest compared to other components in artificial systems. The latest advance in control devices is related to cyber systems. The core technology of control devices has evolved through a mechanical → electromechanical → digital → software → cloud route. The continuous introduction of new technologies into control systems finally achieves CPS, as shown in Figure 11. The evolution of the control device is consistent with the fusion and integration of the administration shell and the physical facility in RAMI 4.0, which is how CPS is constructed.

There are many scenarios driving the development of intelligent systems (e.g., intelligent manufacturing) [45]. Nowadays, intelligent manufacturing is evolving into a new state based on next-generation artificial intelligence. This can be termed new-generation intelligent manufacturing (NGIM) [4]. Traditionally, artificial intelligence has been defined

as a branch of computer science to simulate the thinking processes and intelligent actions of humans. However, new-generation artificial intelligence extends traditional digital intelligence to big-data intelligence, crowd intelligence and human-machine hybrid intelligence. These new-generation AI technologies have greater content and can be applied in more domains. For example, big-data intelligence originated from the operation information of cyber systems under the close collaboration among three entities, which cannot be processed by humans, to reveal the mode and inner laws [46]. Crowd intelligence is generated among different entities, and it is hard to determine which one is the controller, and which one is controlled [9].

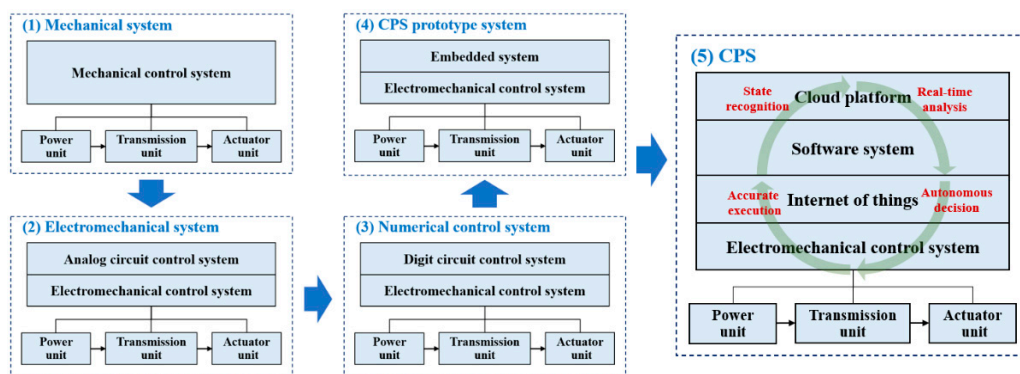


Figure 11. The evolution of control system to CPS.

6. Conclusions

As a demarcation of the past, present and future of intelligent systems, a Tri-X Intelligence (TI) model is proposed in this paper to state the mechanism, factors and connotation of three main entities (conscious humans, physical objects, and cyber entities) including single-X intelligence, two-X integrated intelligence and three-X complex intelligence. Every single entity shows primitive intelligence. Two-entity integration creates integrated intelligence. Three-entity fusion generates advanced intelligence. The intelligentization mechanism of artificial systems continuously converts human intelligence to machine intelligence via different channels and interfaces. With the increasing use of machine intelligence, humans will gradually play a less significant role in intelligent systems. However, human intelligence will keep influencing artificial systems in the form of software/algorithms to drive intelligent systems. Therefore, we cannot take humans out of the systems given the accelerating development of technology. The key to success is to adapt humans to new work environments, i.e., not to replace but to enhance. According to the Tri-X Intelligence (TI) model, humans need to think more about how to collaborate with cyber systems rather than training operators to work like computers.

The proposed Tri-X model (e.g., HCPS) will integrate the intelligence in a the complex system with a combination of human-cyber-physical and machine subsystems. In future research, modeling intelligence in experiments or simulations is critical. Different cognitive architectures, such as LIDA of Stan Franklin, ACT-R of CMU, SOAR from the University of Michigan, Subsumption Architecture of the MIT AI lab, or BDI (belief, desire and intention) provide structure to create intelligent actions. Different methodologies like neural networks, genetic algorithms, simulated annealing, the Monte Carlo method and swarm intelligence are approaches to create actions that could result in intelligent behavior. The ultimate goal of HCPS, or Tri-X modelling and implementation, is to achieve effective and efficient symbioses among humans, cyber systems and physical systems.

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