A Survey of Cognitive Architectures in the Past 20 Years

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***Abstract*—Building autonomous systems that achieve human level intelligence is one of the primary objectives in artificial intelligence (AI). It requires the study of a wide range of functions robustly across different phases of human cognition. This paper presents a review of agent cognitive architectures in the past 20 year's AI research. Different from software structures and simulation environments, most of the architectures concerned are established from mathematics and philosophy. They are categorized according to their knowledge processing patterns—symbolic, emergent or hybrid. All the relevant literature can be accessed publicly, particularly through the Internet. Available websites are also summarized for further reference.**

***Index Terms*—Agent, artificial intelligence (AI), cognitive architecture (CA), survey.**

I. Introduction

CREATING general human-like intelligence is always one of the initial goals in artificial intelligence (AI). To do this, great effort has been put forward to study the patterns that how we sense, behave, decide and perhaps the most important—think. Cognitive architecture (CA) research is a promising theme in this area that models the main factors participated in our thinking and decision and concentrates on the relationships among them. In computer science, CA mostly refers to the computational model simulating human's cognitive and behavioral characteristics. Despite a category of loose definition, CAs usually deal with relatively large software systems that have many heterogeneous parts and subcomponents. Typically, many of these architectures are built to control artificial agents, which run both in virtual worlds and physical robots.

Research on CA has been conducting persistently for decades. This constant devotion has brought us a large amount of achievements currently—more than one hundred architectures available to our knowledge. Moreover, these achievements also display broad diversity at multiple levels: underlying theoretical assumptions, inspiration, motivation, requirements, methodology, structure, and technology. Architectures also target a diverse set of cognitive functions, although learning, reasoning, planning, and memory seem to be more common than others. The primary objective of this paper is to take a broad overview of the latest CA research, so that it can provide scholars an inventory of what have accomplished and lead to a solid starting point of our future study. Similar work was conducted by Chong *et al.* [1], Langley *et al.* [2], and Thorisson and Helgasson [3]. Yet their work merely involves a small part of architectures. Kotseruba *et al.* [4] summarized 40 years of CA research and mainly focused on perception, attention, learning, and application aspects. Despite showing us a macroscopic view of the field, their work has omitted some CAs in specific domains, such as emotion and reflex.

To limit the scope, the CAs reviewed here are mainly emerged in the 21 century and can be mostly achieved via a public source, specifically, the Internet. Due to space limit, the CAs are introduced only from its knowledge generation, knowledge processing, and application. If the reader wants to go further details, he can easily follow the references and other relevant literature. The reviewed CAs focus on the sense of mathematics and philosophy, which means two types of systems are not contained. The first one is the structure at the implementation level, such as the agent's communication module, the database, and the graphical user interface. Despite similar to the CA sometimes, these components in essence belong to the software structure and thus will not be discussed in this paper. The second type is usually referred to as the simulation environment. Although a part of the environments certainly include CAs, they are not generally essential. Rather, these systems are computational platforms for the implementation and validation of various agent models.

The remainder of this paper is organized as follows. According to the cognitive mode which means the way that how the internal knowledge is generated and processed, Sections II–IV summarize three types of cognitive architectures—symbolic, emergent, and hybrid ones.

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Section V further lists the CAs whose websites are available with their cognitive functions. Section VI puts some discussions and concludes this paper.

II. Symbolic Cognitive Architectures

The first dominant kind of CA is called symbolic systems, which is an important research area in traditional AI. This type of agents maintains a consistent knowledge base (KB) by representing the environment as symbols. Formal logic is usually introduced to conduct reasoning in each sensation-decision-actuation cycle. Despite the subsequent emergence of fuzzy logic, classic symbolic CAs are deterministic and applied to the system control, such as robotics.

4-D Real-Time Control System (4D/RCS): The 4D/RCS architecture is developed since the 1980s for the military unmanned vehicles [5], [6]. It is a three-tiered structure. The top behavior generation layer converts original missions into concrete actions. The middle world modeling layer processes symbolic data and segmented images. The bottom sensory processing layer monitors the actuator and feedback its situation to the sensory. There is also a global value judgment to evaluate the decision and plan candidates.

Adaptive Control of Thought-Rational (ACT-R): ACT-R is a popular architecture and still being researched actively. Its models the knowledge exploration and intelligent behavior production [7], [8]. The latest version involves a declarative module, an intentional module, motor modules, and sensory modules. ACT-R uses a buffer in each module with declarative knowledge called "chunks" (different from Soar which will be discussed later) to simulate short-term memory (STM). Its long-term production memory, held by the declarative module, keeps the past experience that can be used to estimate the behavioral cost and probability of success. During each decision cycle, the agent executes the production with maximum utility.

Adaptive Dynamics and Active Perception for Thought (ADAPT): ADAPT is specifically designed for robotics. It concurrently deals with a lot of executable schemas with perception and planning [9], [10]. In contrast with many other CAs, agent is endowed with the ability of active sensation, considering the top goal, the context and even the lower raw sensory data. Also, robots with ADAPT architecture are able to conduct reasoning based on concurrent real-time behaviors with an ultimate parallelism.

Architecture for Real-Time Dynamic Inspection Systems (ARDISs): ARDIS is a knowledge-based architecture for expert systems. It adopts the CommonKADS methodology and is mainly applied to inspect the industrial laminated materials [11], [12]. In each cycle, agent first outlines a skeleton as a seed for subsequent expansion. Then the expansion configures an inspection solution and finally, the agent modifies the configuration by its received images.

Belief-Desire-Intention (BDI): BDI originally stems from the main thought of the philosopher Bratman [13]. Since then it becomes one of the most popular models of agent decision making. BDI tends to establish a complex task oriented system that can perform effective reasoning in a dynamic situation [14]. BDI agent grounds the reasoning on its internal "mental state." Such mental state, as the BDI named, is related to three parts—beliefs, desires and intentions. Thus, this type of agent is referred to as an "intentional system" as well.

Control Architecture for Robotic Agent Command and Sensing (CARACaS): CARACaS concentrates on the complex task involving human and machine simultaneously [15], [16]. A kernel system that incorporates habitat behaviors forms the main part of CARACaS. The autonomous coordinated robots provide such habitat behaviors. Shadow behaviors play a media role to smooth the coordination. These behaviors convert the mission into global activities or other essential resources. Each participated agent, either human or robot, is treated without distinction but marked with a competence score. The score is used to record activities of others and estimate the progress of the mission.

CA, Specification, and Implementation of Mental Image-Based Reasoning (Casimir): Casimir computationally models human's cognition of relative positions using spatial analogical and pictorial knowledge [17]. It contains a working memory (WM), a long-term memory (LTM) and a diagram processor. Ontology is built in the LTM to organize abstract knowledge and is available by the current goal decomposition. In WM, experience from the LTM and the latest perception are integrated for further exploration and reasoning. Image modification and inspection are conducted by the diagram processor to update the internal KB.

Cerebus: Cerebus tends to manipulate the robot's behavior from a high level cognition. It benefits from sensors and motors that focus on behaviors and networks maintaining semantic knowledge and deduction [18], [19]. Cerebus is able to complete tasks and answer questions in parallel. Its reflective knowledge is first transmit to the LTM and then restricted to the actions and signals within the system. Its behavior is called higher order behaviors with parameters.

Context Hierarchy-Based Adaptive Reasoning Self-Motivated Agent (CHARISMA): CHARISMA is designed to grow a virtual civilization-inspired vying society [20]. Two hypotheses are introduced during its development. First, agent's motivation greatly influences on self-maintaining, knowledge evolution, skill learning, and environment adaptation. Second, knowledge representation, stored in a semantic network, is modeled as a time-variant structure so that new skills both from past personal practice and social communications can be acquired. Overall, CHARISMA contains intrinsic motivation, reflex, active/passive perception, sensory buffer, WM with conscious/unconscious concentration, and preservation drives.

Cognitive Symmetry Engine: Cognitive symmetry engine combines data analysis of sensors and actuators with abstract heuristics [21], [22]. Symmetry tokens are extracted from the sensor and actuator data, and are analyzed to generate high-level concepts. Basically, the architecture involves short-term perception memory (STPM), short-term motor memory (STMM), LTM, and modules of action, perception, context, and action selection. In cognition, sensor data arrives constantly to form symmetry characterizations in STPM. The action selection module determines next steps according to current STPM, STMM and LTM.

CoJACK: CoJACK tends to capture the variation among human behaviors [23]. Based on BDI architecture, it includes a layer played as an arbitrator to maintain continuous reasoning and planning. In high-level planning, situation representation, behavioral candidates, prediction, personality, and emotion are all taken into consideration. Memory is represented as declarative chunks and can be activated with a threshold. Procedural knowledge for reasoning is delineated by a graphical plan. CoJACK is applied in virtual reality and military scenarios.

Companions: Companions concentrates on evolutionary intelligence with social intelligent agents. It includes deductive operation, adaptive reasoning, comprehensive conceptual knowledge, parallel implementation, hierarchical leaning, persistent operation, and social interaction [24], [25]. Deduction matches current situation with internal knowledge, and stores new memory. Comprehensive conceptual knowledge encodes rules as ontology. Adaptive reasoning tracks and explains the inference process. Parallel implementation provides concurrent computational mechanism. Hierarchical learning determines the goals to be pursued. Persistent operation supports comprehensive sessions, and social interaction facilitates the communication with other agents.

CORTEX: As a successive version of RoboCog [26], [27], CORTEX is developed for social robots. It is a three-layered structure—perception, simulation, and action execution. The kernel of CORTEX is a graph-based network called deep state representation (DSR), which encodes knowledge in different levels. DSR is accessible and can be updated by perceptual agents through the modification of the truth-value of logic statements or the numerical value of properties. Deliberative agents can also put action/state tuples planed from the goal to the graph. Such tuples will stimulate the action generation agents to cooperate with each other.

Distributed Integrated Affect, Reflection, Cognition (DIARC) Architecture: DIARC is designed for natural and reasonable interaction between human and machine. It tries to let the agent be capable of processing natural language, analyzing dialog structure, recognizing emotion, communicating in nonverbal form. Robustness is also emphasized for fault tolerant when the system breaks down [28]. Formally, there are three primary modules: 1) goal manager; 2) heuristic inference; and 3) analogical reasoning. Goal manager receives mission and combines actions. Heuristic inference conducts reasoning. Analogical reasoning filters suitable actions. Based on DIARC, some other extensions are studied later [29], [30].

Distributed Practical Reasoning Architecture (DiPRA): DiPRA refers to BDI but emphasizes the distinctions between offline planning and online action, integration of different reasoning and deliberation, and allocation of limited resources [31], [32]. Beliefs and actions, plans, goals, and reasoner are all contained in an intentional layer, which determines the plan according to current intention. A sensorimotor layer generates various particular schemas. Such schemas can be run in parallel to conduct actions in a expected way and estimate the subsequent influences. DiPRA is validated as a simulated robot that plays a "thief" role in a guards-and-thieves case.

Defense Science Organization-CA (DSO-CA) Architecture: DSO-CA tries to combine extensive knowledge from low-level sensory information, high-level contextual information, and visual input to perform realistic reasoning [33], [34]. Perception, execution, affection, integration, and actuator control are mapped into five modules at the top level. The affection further involves four components: goal monitor analyzes the top mission to subgoals and dynamically evaluates their progresses. Selector determines the behavior. Relay module correlates and updates distributed knowledge. Episodic module extracts new memory from experience. DSO-CA is used in image processing particularly.

EMILE: EMILE considers different emotions with influence on planning and reasoning [35]. It partitioned planning into five independent phrases. At first, plans are produced to assemble actions with further goals. Second, the agent will evaluate the goals with its mental and physical states. Third, each evaluation result will be associated with a score and an overall emotional state will be achieved through the results. Finally, the emotions are adopted to determine the behavior selection. Objectively, EMILE gives a general explanation of the relationship between the plan representation and the emotional state processing.

Elementary Perceiver and Memorizer (EPAM): EPAM is a general architecture with immediate, short-term and LTM [36], [37]. The LTM consists of procedure memory, declarative memory, algorithms, and explicit knowledge. The algorithm and knowledge are arranged with indexes in a network. Auditory and visual patterns, in the STM, are linked with specific perceptions and to produce expected behaviors. In the immediate memory, concrete conditions for behavior activation are identified from the visual and auditory sensory data. EPAM is applied in a wide variety of experimental paradigms including classification learning and serial anticipation learning.

Executive-Process/Interactive Control (EPIC): EPIC aims to model the object searching process of visual input and the interaction between human and environment [38], [39]. In each cognitive cycle, event objects are produced from sensors and allocated to different cognitive processors for successive activation of formal logic rules. The rules are dynamically maintained in the long-term and productive memory. When the objects match the preconditions of associate actions in vocal and manual processors, related behaviors are performed subsequently. Software of EPIC can now be achieved freely.

Grounded Layered Architecture With Integrated Reasoning (GLAIR): Based on BDI architecture, GLAIR is a tiered structure developed for real, virtual, and simulated agents in multiple domains [40]. Its top knowledge layer includes the latest representation on current environment and plays several cognitive functions. Its bottom sensory-actuator layer monitors and controls the executor of software robot. The middle perceptual-motor layer provides the knowledge layer symbolic and behavioral base, and extracts the actions from the bottom layer to abstract candidates. It also bridges the top and bottom with specific communications. In execution, GLAIR agents mostly conduct sensation-reasoning-action loops.

George Mason University Biologically Inspired CA (GMU-BICA): GMU-BICA is developed for computer-aided educational systems. In a high level, GMU-BICA represents the knowledge both in symbolic and connectionist ways [41], [42]. Its memory involves working, episodic, semantic, and procedural memory. The WM maps neural information into virtually mental states. The episodic memory maintains long-term experiences. The semantic memory stores schemas objects and environment. And the procedural memory keeps patterns of neocortices. A driving engine and a reinforcement learning system links the memories with each other.

ICARUS: ICARUS is a tiered system with analytical knowledge representations and task completion skills. The analytical knowledge is explained by other objects and relationships. The skills are the concrete measures for specific goals [43], [44]. Each recognize-act cycle is composed of two independent stages. During the recognize stage, sensory data are kept in perceptual buffers and are compared with intrinsic knowledge. Matched pairs are stored as the latest perception. In the act stage, the agent searches the solution from top-down. The solution is defined as the skill sequences whose preconditions are satisfied but the actions are not performed. Finally, these actions are integrated to be conducted physically.

Integrated Cognitive Universal Body (iCub): iCub primarily concerns about individual exploration and social interaction. It originally involves locomotion, gaze control and reaching, but later introduces episodic and procedural memories. There are 13 modules in the architecture now [45], [46]. The attention selection, exogenous salience, egosphere, and endogenous salience comprise the perception system. The gaze control, vergence, reach and grasp, and locomotion are integrated as the execution system. Episodic and procedural memories construct the expectation and adaptation. Motivations are formed by the affective state component.

Improved Performance Research Integration Tool (IMPRINT): IMPRINT is developed for computer-aided human performance evaluations. It is grounded with the Micro Saint task network that models the environment [47], [48]. Cognitive functions are categorized into several levels. At the top, original mission is converted into subtasks with appropriate logics. At the bottom, IMPRINT uses ACT-R to model its atomic thought. Goals in ACT-R are directly integrated from the IMPRINT tasks, and can be represented as ACT-R models.

Methodology for Analysis and Modeling of Individual Differences (MAMID): Heterogeneity is mainly considered in MAMID as the result of personality (trait) and transient emotions (states). Different personality styles are modeled as processing-biases. It deems the desired characteristics as content-biases [49]. Five modules lie in the kernel. The perception preprocessing dynamically updates the current state of the world. The attention selects perceptual cues for further processing. The situation assessment combines historical beliefs with the latest perceptual cues. The behavioral selection determines appropriate actions for future execution. And the execution and monitor handle the feedback from environment.

MicroPsi: MicroPsi adopts Psi theory to model the interaction between motivation and emotion [50]. Such interaction is often reflected as the action regulation in human behavior. Basically, MicroPsi incorporates all the cognitive functions into a motivational structure. Those functions involve sensory data analysis, approach and effect analysis, action execution, personality/emotional modeling, reinforcement learning, simple neural learning, and memory maintaining. MicroPsi is implemented in robot control scenarios.

MusiCog: MusiCog tends to support the research of music representation, recognition, and generation [51], [52]. There are four main parts. The perception module preprocesses the musical input and separates it into stream segments. The WM matches melodic patterns with knowledge and stores similar ones. The LTM maintains tiered musical voices and acquires new experiences concurrently. And the production module finally synthesizes the melody as its output. The output is further directed back to perception to form a feedback loop. MusiCog is implemented in the ManuScore interactive composition environment.

Nonaxiomatic Reasoning System (NARS): Assuming that intelligence is the environment adaptation with insufficient knowledge and resources, NARS emphasizes real-time working, limited computational capacity, and various task adaptations [53], [54]. It is suitable for learning, answering questions, and planning. The major components include a memory system, a reasoning engine, a task buffer, input/output channels, and a control center. In a cognitive cycle, agent chooses a concept from memory and gets a task. Then it stores the related beliefs in the buffer, and processes the tasks with feedback information. NARS is applied in decision-support system for crisis response [55].

Novamente Engine: Novamente Engine concerns multiple AI subfields [56], [57]. Its main elements are nodes, links, mind agents, mind OS, maps, and units. Concepts and objects are represented as symbolic nodes. Links among nodes or other links portray the relationship of concepts and objects. Mind agents are the containers for knowledge update and logical reasoning. Mind OS provides the system a parallel computational environment. Maps store different types of knowledge. A unit is an entity including maps, mind agents, and particular cognitive functions. Novamente engine is implemented in the second life virtual world [58].

OpenCogPrime: OpenCogPrime is for artificial general intelligence and established on a weighted labeled knowledge hyper-graph, called the atomspace. In essence, the atomspace is a probabilistic logic network that supports all the cognitive algorithms [59], [60]. Chain reasoning is activated based on deduction rules. Forward and backward chaining are both adopted to add new results to the KB and to perform particular propositional check. OpenCogPrime is still being developed recently and needs to be further implemented.

Performance Moderator Functions server (PMFserv): PMFserv investigates the influence of biological stress, personality and culture, and social interactions upon individual and group decisions [61], [62]. The biology component determines behaviors and predicts effects for specific situations. The personality/cultural module categorizes human emotion into 11 pairs. It is linked with biology, perceptual, and other modules. The social module endows other agent with trust degrees and introduces their impacts in decision-making process. And the cognitive component plays as a container that all the emotions, memories, object representations are combined to determine successive actions for maximum expected rewards or utilities.

Pogamut: Pogamut aims to build a 3-D virtual world with ACT-R human cognition model [63]. In contrast to ACT-R, Pogamut develops action selection mechanism (ASM), LTM, STM, and goal structures [64]. The STM has four functions: 1) encoding objects and entities of current world; 2) extracting related knowledge in LTM; 3) decomposing goals into subtasks; and 4) estimating other tasks. The LTM keeps tasks and experiences in a knowledge tree. And the ASM is calculated according to the level that an action can achieve the goal and task.

Polyscheme: Polyscheme focuses on multidomain knowledge representation, reasoning, planning, as well as their integration to model intelligent behaviors. The primary parts are specialists, attention buffer, and focus manager [65], [66]. Beliefs are kept as specialists to support the higher reasoning and planning. Dempster–Shafer theory is used to quantify the probability and agent's confidence of an event. Polyscheme plays a three phrase cognitive cycle. The top focus manager chooses specialists to extract opinions as candidates. The specialists collaborate to reach a consensus. And the result expertise will be diffused for current problem.

Recognition-Primed-Decision-Enabled Collaborating Agents Simulating Teamwork (R-CAST): R-CAST aims to improve the efficiency of teamwork by considering systemic flexibility, collaboration adaptability, and context-based reasoning [67], [68]. Three components form the core. The RPD-based decision making module maintains different beliefs, the past experiences, and the perception of environment. The teamwork manager facilitates the collaboration among different agents to promote the achievement of a mutual goal. The task work manager operates on internal activities for subtask completion.

REflexive Architecture for PERceptive Agents (REAPER): REAPER is a general CA for mobile robot [69]. It concerns about internal state transferring, visual and auditory perception, language and speech processing, monitoring, navigation, and interaction. It also provides multiple functions of environmental sensation, reflexive behavioral generation, motor and actuator control, and also debugging for the developers. Each module, except the central controller, has its own program cycle after initialization. The module cycle starts from an idle state and the controller judges whether the modules are all assigned an action. If so, execution will begin concurrently. If not, they will be marked with an idle token and waiting for new assignment.

Reflective Evolutionary Mind (REM): REM is an instant-based reasoning architecture which treats human's intelligence as tasks, methods, and knowledge [70]. Task is the fundamental ultimate goal and is represented as proposition knowledge of past, present, and future world's states. Methods delineate the manipulation sequence with their transition process. Knowledge provides the basis of chain reasoning. In a computer war strategy game, REM is validated and plays well in many task traces [71].

State, Operator, and Result (Soar): Soar is an early classic symbolic architecture and still being improved currently [72], [73]. Apart from perception and action, it primarily contains a WM, an LTM, and a decision procedure. Beliefs of current perception are stored in the WM. The LTM holds semantic network, past experiences, and procedural memory. In each execution cycle, current perceptions beliefs trigger production rules to propose operators. Then the decision procedure selects an operator to execute according to its knowledge and other available resources. If there are no operator candidates or such kind of knowledge, Soar will create an impasse and randomly try one possible operator in another problem space.

III. Emergent Cognitive Architectures

The second type of CA is named as emergent CA. Based on the biological structure of the brain, they try to "reproduce" the process of human cognition from bottom up. Emergent CA usually adopts hierarchical structure. The bottom level simulates human cortex and neurons by artificial neural network, while the top level simulates the active consciousness. Environmental knowledge and basic behaviors are first formed at the bottom concurrently. Then the active selection mechanism at the top level will solve their conflicts according to current available resources and choose a suitable behavior to perform. Emergent CAs are able to deal with uncertain cognitions. Thus, they are comprehensively applicable in many domains, specifically in pattern recognition and image processing.

Adaptive, Reflective Cognition in an Attention-Driven Integrated Architecture (ARCADIA): ARCADIA is proposed recently with emphasis on attention in perception and cognition [74], [75]. It involves low-level movements, temporary knowledge (called uninspected processing), and focused object. In the cognitive process, accessible knowledge with attention is sent to the low-level component. The components connected to sensors provide perceptual knowledge, while others retain such information. Actions are generated by all the components as long as they can be determined according to the input. The focus element and accessible knowledge can be transmitted to other low-level components in the next cycle.

Attentive Self-Modifying (ASMO): ASMO stems from a project exploring the mechanism of attention, self-adjustment, and awareness in robotics. It also attempt to solve practical problems in its implementation [76]. The hypothesis behind ASMO is that our mind is founded on a large collection of autonomous information processes. Each of these processes is associated with an attention value. Such attention value can be assigned by the system designer, or learned by the machine itself using various AI algorithms. The results of information processes can lead to different actions of different motors. The processes with high attention values will play dominantly and their actions will be conducted.

Brain-Based Device (BBD): Based on computational neuroscience, BBD tends to simulate neural activities in microscope. It assumes that the machine needs an artificial neural network with brain structure to dynamically monitor its behavior; the machine needs to be placed in real world to test its adaptability; and its behavioral data must be comparable with historical results [77]. BBD can actively explore in dynamic world, simulate the brain's activities, and update the agent's memory. In addition, this architecture introduces feedbacks to adjust its behaviors from its evaluation system. In application, BBD is constructed in Darwin VIII for visual object recognition [78].

Brain-Emulating Cognition and Control Architecture (BECCA): BECCA focuses on brain cognition and control in multiple task completion [79], [80]. It is mainly comprised of a feature generator and a reinforcement learner. The former explicitly represents the features in the problem space. While the latter learns the models by maximizing the received reward. The main cognitive cycle involves perception, learning, planning, and actuation phrases. These phrases can be further decomposed into six major steps: 1) evaluating the perception and reward; 2) maintaining the feature basis; 3) interpreting the perception; 4) estimating probable results; 5) choosing an action; and 6) updating the representation of current world.

Conscious and Emotional Reasoning Architecture-Cognitive Robotics Architecture Neurologically Inspired Underlying Manager (CERA-CRANIUM): CERA-CRANIUM combines CERA (a tiered subsystem for control mission) and CRANIUM (a container for parallel micro computation) to ubiquitously model consciousness [81], [82]. In CERA. The low level sensory layer receives perception data and sends controlling strategies. The physical layer manages sensors and actuators. The mission layer keeps specific goals and generates typical behaviors. The highest core layer provides primary cognitive functions. CRANIUM supports the concurrent unit computation of CERA. And CERA, in turn, uses these micro processes to complete dynamical responses.

Cognitive Systems for Cognitive Assistants (CoSy): CoSy comes from a European project that tries to shed light on the construction of physical entity with high autonomy. It involves knowledge representation, perception, learning, planning, reasoning, etc. The overall architecture is designed as a loose structure for coordination of flexible and parallel components. Components usually cooperate with each other to achieve global missions, and they also compete for shared resources. A part of these subarchitecture can be further decomposed and they organize their knowledge as ontology [83].

Distributed Adaptive Control (DAC): DAC is developed to solve the problem of interaction among expectation, prediction, attention, and memory of actual and software robot [84], [85]. From bottom to top, four layers—somatic, reactive, adaptive, and contextual—are arranged, respectively. The somatic layer contains interfaces of agent's various physical components. The reactive layer interprets perceptual data into low-level actions. The adaptive layer selects higher-level action with concern of active motivation and reward estimation. The top contextual layer stores the long-term experiences and conducts abstract planning and reasoning.

Hierarchical Temporal Memory (HTM): HTM is another architecture from computational neuroscience to simulate the brain's function of recognition and categorization [86]. Artificial neurons are embedded in different layers. Each neuron node is connected with others (from its own layer and adjacent layers) and contains similar cognitive functions. Perceptual information is diffused from bottom up. The neuron in higher layer receives stimuli from a great many nodes in low-level. Thus, the final response is given by a few highest nodes.

Ikon Flux: Ikon Flux emphasizes that the machine should have self-programming capability to achieve the general intelligence [87]. Thus, it tries to learn new models from its behaviors. These models are evaluated by the reward and used to control actuators. Low-level self-programming adjusts the models to the missions. Whereas high-level self-programming monitors the low-level ones and completes meta-learning functions. With constant running, new models are added and are semantically organized by an independent component.

Leabra: Leabra is developed from computational neuroscience for visual image processing. It has biological foundations and simulates three brain parts: 1) inferotemporal cortex (IT); 2) extrastriate cortex (V2/V4); and 3) primary visual cortex (V1) [88], [89]. In a recognition cycle, visual signal is first sent to a group of artificial neurons which play the function of retina. The output signal is used by V1 to extract spatial features that are encoded in a neural network. From the features, V2/V4 and IT layers are able to analyze the object with much fewer neurons and match the features with the agent's own knowledge. In essence, Leabra can be viewed as a construction of forward visual processing in the brain.

Learning Intelligent Distribution Agent (LIDA): LIDA is a popular computational framework in artificial general intelligence [90], [91]. Its perceptual memory stores messages from environment and self-awareness. Global workspace contains the latest and unforgotten perceptions. Episodic memory includes the past experience. Attentional memory simulates the attentions. Action determination and sensory-motor memory propose and select final actions. In a cognitive cycle, agent initially updates its beliefs and mental state. Then the perceptual contents compete the attentional resources. Finally, the agent selects one action to execute in the next period. The overall process can be viewed as a comprehension, deliberation, and actuation iterative cycle.

Multilevel Darwinist Brain (MDB): MDB aims to build a system for adaptation to time variant environment with restricted resources [92], [93]. It is grounded on three evolutionary parts: 1) the world model which represents the surrounded world and collects the effects of previous behaviors; 2) the internal model, which delineates the distinctions between the mental states before and after behavioral actuations; and 3) the satisfaction model, which evaluates and estimates the reward of generated actions. Learning is implemented in every cycle using heuristic algorithms. MDB is experimented on a Sony AIBO robot and a Pioneer 2 robot.

Sensory-Motor, Episodic Memory and Learning, and Central Executive (SEMLC): SEMLC emphasizes the global management of multiple cognitive functions [94], [95]. Its subsystems are called sensory-motor, episodic memory and learning, and central execution. In sensory-motor, perceptual information, motor control dynamics, and emotional rewards are collected. Objects with semantic relationships, new knowledge and experiences are maintained in episodic memory and learning. The most important central execution module facilitates the cooperation of other components.

Shruti: Shruti has a biological foundation with ability to encode objects, entities, types, relations, and episodic knowledge in a unified network. It can conduct near real-time reasoning and prediction [96], [97]. The role nodes in the knowledge network carry concrete knowledge while the collector nodes, both positive and negative, control its degree of trust or skepticism. Enabler nodes search beliefs to explain current facts. Shruti is implemented in a pilot system, and can filter the most suitable explanation in a competitive way.

IV. Hybrid Cognitive Architectures

The third type is called the hybrid architectures. This type usually adopts hierarchical structures as well, and contains both behavior emergence from bottom up and direct symbolic processing. They have multiple application domains, ranging from knowledge discovery, computational neural science to artificial general intelligence.

Cortical Capacity-Constrained Concurrent Activation-Based Production System (4CAPS): As a cognitive neuro-architecture, 4CAPS inherits the features from 3CAPS [98]. It concentrates on natural language processing, problem solving, spatial knowledge representation, and task performing. Information processes are concurrently computed and monitored by control centers for the load balance. Such processes can simulate various functions related to the areas of human brain. 4CAPS is still being studied and is implemented by ANSI Common Lisp [99].

Conscious Emotional Learning Tutoring System (CELTS): CELTS introduces transferring learning and memory with analogical information [100]. It implements emotional unit, attention, learning, memory system (declarative and temporary), self-awareness, perception, and action repertoire to construct the cognitive cycle [101]. Agent will first extract the representation of its surrounded world and keep the perceptual results in its temporary memory. Then sensation-action pairs are connected and evaluated to select behaviors and spread them into actuators. Stress is imposed on the emotional signals and responses in order to improve intelligence.

Chunk Hierarchy Retrieval Structures (CHREST): Generally, CHREST involves STM, LTM, and input and output (I/O) modules [102]. It places perception and learning in a central position. The I/O module encloses basic visual signals, audio signals, and behavioral units. Chunks, held by STM and LTM, are produced via evaluation of signals and units. The evaluation is according to how familiar they are for the agent. In contrast to other architectures, such as ACT-R and Soar, where knowledge is differentiated to be declarative, procedural, or semantic, CHREST treats the memory as a whole.

Connectionist Learning With Adaptive Rule Induction Online (CLARION): As a popular hybrid architecture, CLARION tries to incorporate most cognitive aspects [103], [104]. It distinguishes abstract and concrete knowledge, where concrete knowledge is easier to obtain and gets more attention than the abstract one. Action-centered subsystem (ACS), motivational subsystem (MS), nonaction-centered subsystem (NACS), and meta-cognitive subsystem (MCS) are the four subsystems. Procedural and declarative knowledge is kept in ACS and NACS. The ACS performs behavioral control and supports NACS. The MS maintains goals and motivations for active cognition. The MCS conducts learning and selection and evaluates the performance of other components.

Cognitive Networks of Tasks/iGEN (COGNET/iGEN): As indicated by its name, COGNET/iGEN is a combined framework to model human cognition with a symbolic memory and emergent attention. COGNET is a container that holds multiple agents via its application program interfaces. iGEN is a development tool for debugging and testing [105], [106]. Perceptions are represented by symbols in the LTM. Multiple tasks are generated and kept in parallel and will be chosen by the attention in high level. Learning is also conducted separately in the memory.

Synthesis of ACT-R and Leabra (SAL): SAL combines ACT-R and Leabra to exploit the advantages of symbolic representation and emergent neural cognition [107], [108]. In general, ACT-R deals with the main cognitive cycle that links different components to perform reasoning and problem solving. While artificial neural network in Leabra stores explicit knowledge and actions. Thus, ACT-R manages "macro" process of sensation-actuation and validates the behaviors according to human aggregate data at the top, while Leabra introduces "micro" restrictions that guide the cognition in a biological mode at the bottom.

Simulation of the Mental Apparatus and Applications (SiMA): SiMA tends to create plausible and reasonable motivation in human decision and behavior. It adopts the psychoanalytic drive theory to model personality and emotions [109], [110]. SiMA has three layers. At the bottom is the basic activity layer of neural network, which receives sensory signals and motor control commands from higher layers. At the top is a symbolic system that plays multiple cognitive functions and contains KB. The middle layer bridges the former two by converting the low-level perceptions into symbolic concepts for the higher system, and vice versa. SiMA is applied in case-driven agent-based simulations.

V. Open Sources and Websites

To compare the reviewed architectures more intuitively, we list the cognitive functions of each CA in Table I. Some of them have established their websites, which collect the related research achievements, such as project introductions, publications, source codes, and forums. These open sources have tied scholars and engineers from different areas together and facilitated the further research as well as application to a great extent. In addition, the CAs are summarized by their

TABLE I
COGNITIVE ARCHITECTURES WITH WEBSITES

Abbreviation	Perception	Actuation	Memory	Reasoning	Learning	Attention	Emotion	Planning	Interaction	Motivation	Proposed year	Website
4CAPS	√		√	√	√						2006	http://www.ccbi.cmu.edu/4CAPS/index.html
4D/RCS	√	√						√			2000	(Not available)
ACT-R	√	√	√	√	√	√					2004	http://act-r.psy.cmu.edu/
ADAPT	√	√						√			2004	(Not available)
ARCADIA	√	√	√			√					2015	(Not available)
ARDIS	√	√									2009	(Not available)
ASMO	√	√	√			√					2010	(Not available)
BBD	√	√	√					√			2005	(Not available)
BECCA	√	√			√			√			2009	(Not available)
BDI	√	√	√	√							1998	(Not available)
CARACaS	√	√		√					√		2011	(Not available)
Casimir	√		√	√							2011	(Not available)
CELTS	√	√	√		√	√	√				2011	(Not available)
CERA-CRANIUM	√	√	√	√			√				2009	(Not available)
Cerebus	√	√	√					√			2000	(Not available)
CHARISMA	√	√	√		√				√	√	2011	(Not available)
CHREST	√		√		√	√					1992	http://chrest.info/
CLARION	√	√	√	√	√						1998	http://www.cogsci.rpi.edu/~rsun/clarion.html
COGNET/iGEN	√	√	√		√	√					2000	(Not available)
Cognitive Symmetry Engine	√	√	√								2011	(Not available)
CoJACK	√	√	√	√			√	√			2009	(Not available)
Companions	√		√	√	√				√		2006	(Not available)
Cosy	√	√	√		√			√	√		2004	http://cognitivesystems.org/index.asp
CORTEX	√	√	√	√					√		2014	(Not available)
DAC	√	√	√		√			√		√	2012	(Not available)
DIARC	√	√	√	√			√		√		2006	(Not available)
DiPRA	√	√	√	√				√			2005	http://www.akira-project.org/
DSO-CA	√	√	√	√							2011	(Not available)
EMILE	√	√	√	√			√	√			2000	(Not available)
EPAM	√	√	√		√						1995	http://pahomeschoolers.com/epam/
EPIC	√	√	√		√						1994	http://web.eecs.umich.edu/~kieras/epic.html
GLAIR	√	√		√				√			2009	http://www.cse.buffalo.edu/sneps/Projects/sneps3.html
GMU-BICA	√		√	√							2005	(Not available)
HTM	√	√	√		√						2007	http://numenta.org/
ICARUS	√	√	√	√							2004	(Not available)
iCub	√	√	√			√	√			√	2004	http://macsi.isir.upmc.fr/,http://www.icub.org/
Ikon Flux	√		√	√	√						2009	(Not available)
IMPRINT	√		√	√							2002	(Not available)
Leabra	√		√								2012	(Not available)
LIDA	√	√	√			√					2006	(Not available)
MAMID	√	√	√	√		√	√				2000	(Not available)
MDB	√	√	√		√						2006	(Not available)
MicroPsi	√	√	√		√		√			√	2007	http://www.micropsi-industries.com/
MusiCog	√		√		√						2012	(Not available)
NARS			√	√	√						2013	http://opennars.github.io/opennars/
Novamente Engine	√	√	√	√							2007	(Not available)
OpenCogPrime	√	√	√	√	√	√	√	√	√	√	2013	http://wiki.opencog.org/w/The_Open_Cognition_Project
PMFserv			√				√		√		2001	http://www.seas.upenn.edu/~barryg/HBMR.html
Pogamut	√	√	√								2009	http://pogamut.cuni.cz/main/tiki-index.php
Polyscheme	√		√	√		√					2005	(Not available)
R-CAST	√	√	√	√					√		2008	(Not available)
REAPER	√	√	√						√		2001	(Not available)
REM	√	√	√	√							2001	(Not available)
SAL	√	√	√	√							2008	(Not available)
SEMLC	√	√	√		√			√		√	2011	(Not available)
Shruti	√	√	√	√							2000	(Not available)
SiMA	√	√	√	√						√	2013	(Not available)
Soar			√	√	√						1987	http://soar.eecs.umich.edu/

proposed years, shown in Fig. 1. To our knowledge, ACT-R, CHREST, CLARION, HTM, LIDA, Soar are popular CAs. They are mostly maintained by a team and are constantly improved. Beginners are suggested to start their research by focusing on these CAs because they cover basic aspects of cognitive process and have plenty of references. BDI is another famous CA. But it is only a framework without implementation. Thus, using this architecture needs to introduce concrete

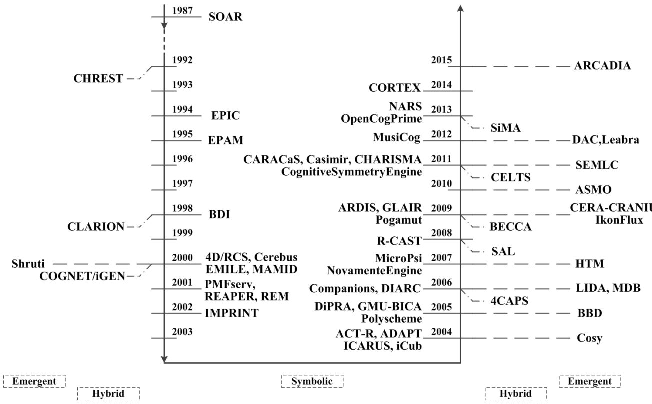

Fig. 1. Temporal arrangement of all architectures.

rules. OpenCogPrime is the most comprehensive CA among the reviewed ones. It involves all cognitive functions. However, it stays at it is early stage and needs to be further researched.

VI. Conclusion

An essential path toward understanding human cognition and developing systems with human level intelligence is to study a wide range of functions robustly across different phases of cognition. Referred to be the CA, this field has attracted a lot of research for decades. This paper gives a broad review of the latest cognitive architectures, which are organized in three categories according to their knowledge generation and processing mechanisms. Available websites are also summarized for further research.

Basically, symbolic architectures are mainly applied in planning, reasoning, and robot control, whereas emergent ones are prevalent in computer vision and pattern recognition. An obvious gap still exists between them. This is probably because symbolic CAs primarily derive from engineering, where deterministic human expert knowledge is used to solve specific problems, while emergent ones are from the exploration of the biological cognitive basis. However, many emerging CAs and agent systems are inclined to adopt a hybrid architecture to merit both advantages simultaneously.

Another less concerned in this paper but highly promising direction is the social cognition and social intelligence based on multiagent system. This field attempts to study the generation and evolution of swarm intelligence. To our knowledge, due to the limitation of computational resources, agent architectures in most of such scenarios, if any, involve several simple rules (referred to be the reactive agent). Complex deliberative process in human intelligent decision-making needs to be further explicitly modeled. Thus, with the increasing computational power, introducing integrated cognitive architectures into multiagent social simulation is probably an issue worthy of study.

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