A Survey of Robotic Agent Architectures

Bora İ Kumova
Active Vision Group, Institute of Computational Visualistics
University of Koblenz-Landau
Koblenz, Germany
kumova@uni-koblenz.de

Samuel Bacha Heye
Department of Computer Engineering
İzmir Institute of Technology
İzmir, Turkey
samuelheye@iyte.edu.tr

[1]***Abstract*—Robotic agents consist of various compositions of properties that are found in their mechatronics, behavioural and cognitive architectures. Common properties of each architecture type serve as criteria for assessing the degree of intelligence of most embodied agent models. Although embodied intelligence has long been accepted for robotic agents, the literature is short on combined evaluations that discuss all properties of all architecture types in one framework. Here we provide a review of existing taxonomies for each type of architecture and attempt to combine them all in a single taxonomy for robotic agents.**

***Index Terms*—Robotic capabilities; behavioural robotics; agent architectures; cognitive architectures; embodied intelligence**

I. INTRODUCTION

With the advent of efficient micro electronics in the 1980s, modest robots with limited autonomous behaviours became popular. Those robots consisted initially of simple mechatronics with primitive task-oriented capabilities. Soon both, mechatronics and artificial intelligence, merged into architectures of embodied intelligence or synonymously embodied cognition [18], with the objective to create smarter robots. We will refer to such architectures as robotic agents.

Agents interact in their environments using sensors and actuators. Similar interaction patterns observed in similar states of the environment are recognised as behavioural capabilities. Cognitive capabilities are patterns in thinking that cannot always be identified by just observing behavioural capabilities. For instance, a real-time planning process of an agent may not be observed in its environment.

Thinking processes may involve concepts at three levels of abstraction: concrete objects of the environment, behavioural patterns and high-level abstract knowledge concepts. Embodied AI is an approach that considers all three abstraction levels, for developing realistic smart systems. We will use the term robotic capabilities in this paper in a broad sense, to refer to mechatronic capabilities that are operated with embodied AI concepts.

Various behavioural or cognitive architectures have been proposed in the literature. Many of them share common capabilities, some emphasise more behaviours and some more cognitive structures, yet extracting out of this rich source hands-on instructions for developing smart architectures turns out to be still difficult. The objective of this work is to synthesise a few architectural properties that are most commonly found in the literature, in order to provide one unifying framework for designing and assessing smart properties of robotic agents.

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The last six decades of AI literature has accumulated overwhelmingly top-down designed symbolic concepts [22]. The idea of noogenesis, the emergence and evolution of intelligence [10], is populating the literature with bottom-up approaches of emergent intelligence only for the last three decades, mostly with probabilistic [8] or neural approaches [52]. Probably the most successful emergent systems by now have become known only in the last decade, with advancements in deep learning [13], [43]. Reflections of emergence on robotic agent architectures is part of the survey too.

First a brief overview of common properties of each type of the robotic agent architectures is introduced, namely mechatronics, behavioural and cognitive. Thereafter we survey related taxonomies and classifications of various architectures. Finally, we suggest a unifying taxonomy for robotic agents, in which some of the criteria of the analysed taxonomies are merging, re-grouped or separated.

II. MECHATRONIC CAPABILITIES

Usually a different mechatronic device is created for any type of interaction with any type of object.

A. Interaction Type

A popular classification of mechatronic devices with robotic purpose separates sensors from actuators. Sensing and acting can be modelled by reading the environment and writing into the environment, respectively [40]. Most interaction devices are sensitive for a specific wavelength only, in which they can either receive or send signals or both.

An actuator with joints, like an arm, is called manipulator [37] and the a tool at the end of the arm is an end effector [31]. Actuators that provide the robot a specific type of mobility, like wheel, leg, wing, are known as locomotion devices [23].

B. Material State of Object

The physical phenomenon, a device is sensitive for, is a further classification criterion, like waves, dynamic mater or static mater. For instance chemicals, like humidity or acid are dynamic, whereas acceleration or collision are measured on static matter.

C. Size of Device

Technically, a device of any size may be mounted on a robot of any size. It is the size of a device that determines the physical scale of operation of the robot, like macro, micro or nano.

D. Elementary Environment

Most devices operate in a specific application domain that is located within a specific elementary environment, like water, earth, gas, vacuum, etc [40] and hence is exposed predominantly to those elements.

III. BEHAVIOURAL PATTERNS

Behaviours are observable patterns of interactions of an agent with its environment. Behaviours may dependent on one another, like higher level behaviours, such as tracking a particular object depend on lower level behaviours, such as navigating safely [30]. The major classification distinguishes reactive from proactive and deliberate behaviour. A further capability is interaction, which is necessary for any type of behaviour (Fig 1). In discussions of behaviour and cognition, we will use the terms robot and agent interchangeable.

A. Reactive

In reactive behaviours, agents do not have an internal symbolic representation of the world and therefore have no means for planning in the world [34]. Reactive agents respond to changes in their environment directly, by applying the first rule of the knowledge base, whose condition matches the change. They strive to make the right responses but their responses are not guaranteed to be optimal since they are based on information obtained from sensors only.

A reflexive behaviour is handled directly on the mechatronics, by a sensor with the capability to directly activate an actuator temporarily. If such sensation is not further processed, then no additional reaction may be observed. In this sense, we distinguish reflexive from reactive, if the first does not reach the knowledge base.

Supporters of reactive architectures believe that the variety of actions an agent can perform is mainly the result of the complexity of its environment, instead of the agent's ability to have a good internal representation of the environment. Thus, some architectures are suggested, like the subsumption architecture, which do not have a symbolic internal representation of the world [8]. The subsumption architecture assumes that the lower-order behaviours, such as reflexive or reactive, do not need to be designed top-down, but may be learned through interactions.

B. Proactive

The capability to reason over alternative inferences, enables for optimising the reaction to a specific sensation, towards predefined goals. Since the outcome of such an optimisation process in the background is usually unpredictable, the behaviour may be observed as proactive.

Proactive agents do not have an explicit world model and therefore cannot perform any planning process, but the world model is implied in their plan execution scenarios.

For instance, possible proactive interactions that an assistive agent might perform on behalf of its user in an office setting, may be following four scenarios: act directly, act indirectly, collect information and remind, notify, ask [35].

C. Deliberative

Deliberate architectures require an accurate and up-to-date internal symbolic representation of the real world. They reason with the symbolic model of the world and can re-initiate planning, as the real world changes, in order to optimise their decisions towards the goals [50].

The hierarchy between reactive, proactive and deliberative (Fig 1) is well known in the literature, where the latter two are usually not distinguished. However we distinguish them here, by clearly separating on the planning capability, as most agent implementations actually do not possess any active planning component, thus according this classification, have proactive architectures.

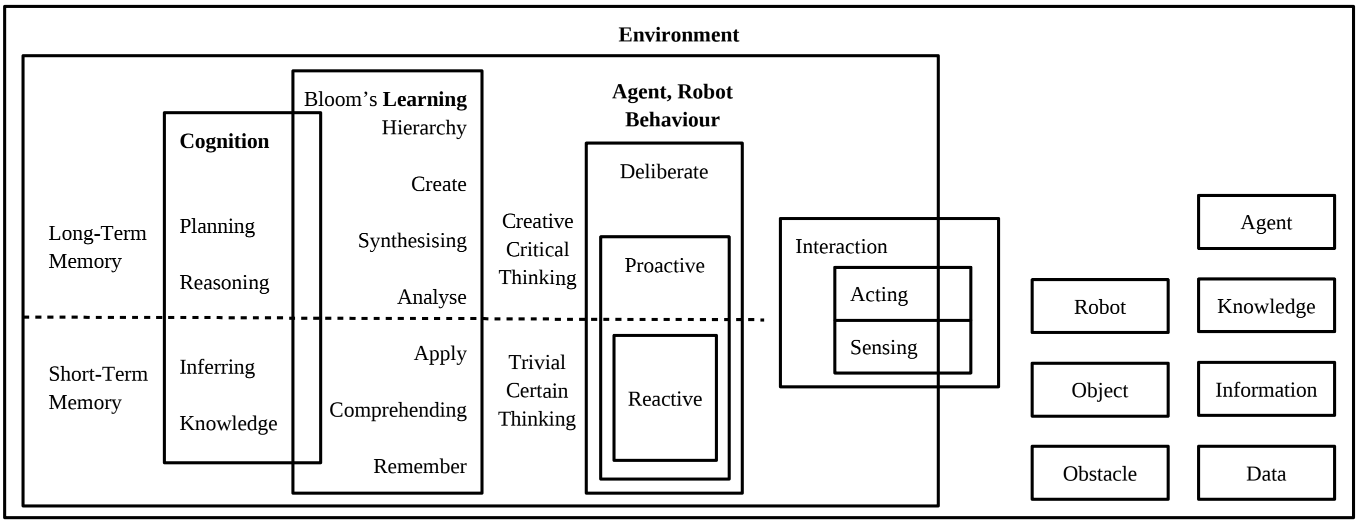

Fig 1. Robotic agent architecture.

D. Interactive

Agents interact with each other or users, in order to synchronize their actions or communicate information [34]. Such interactions are found in multi-agent systems or swarm robotics, which is sometimes referred to as Distributed Artificial Intelligence (DAI). User interaction is necessary, in order for the system to receive commands or to present the results of user-requested services.

An agent's communication capability depends on the chosen medium of communication and its security, the amount and quality of the transferred content etc [31].

E. Autonomy

Autonomous robots are capable of doing tasks without human guidance [51]. They are mostly used to reduce labour costs, in situations where human control is unsuitable or inhuman working conditions [6]. With increasing behavioural capabilities in the hierarchy (Fig 1), an increasing degree of autonomy can be observed.

F. Computational Capabilities

Computational capabilities are related to the way in which a robot performs its computation. They depend, among others, on the processor and algorithms [19] used [31]. Some robots may have limited computational capabilities, but can perform tasks more efficiently in parallel, when deployed in groups [42].

G. Modularity

Modular robots are composed of several reconfigurable components, which combined provide the overall functionality. Mechatronic modules are devices that can be mounted to each other, rather than each being mountable only on a base component. Software modularity does not only increase the efficiency of software engineering, but also the mechatronic modularity, if embedded software is modular too.

Some advantages of modularity are, reconfigurability of the same modules, for achieving different functionalities, the ability to add new components that provide new functionality, easier maintenance since defective modules can be replaced with healthy ones and more reliability, since it is possible to use duplicate modules, where one of them is guaranteed to work, if others fail [29].

H. Operational capability

Operational capabilities refer to those capabilities a robot exhibits after it is deployed. They depend on factors like how long the robot takes to enter a ready state or how long it can perform its tasks without running out of resources or without failure [40].

I. Hybrid Patterns

The architectures we have seen so far have their own limitations [34]. Architectures of various compositions of the above capabilities result in hybrid behavioural patterns. For instance, reactive agents have difficulty carrying out goal-directed actions, while deliberate agents have limited reactivity. It is possible to build a hybrid system that has a combination of the desired properties from the different architectures using layering, where a number of interacting layers is used, each providing a unique functionality.

IV. COGNITIVE ABILITIES

Cognition allows robots to predict the future based on their past experiences [48]. Thus, it allows them to adapt to new environments and to make better decisions by understanding the probable outcome of their actions.

In addition to their use for better understanding the human mind, cognitive architectures also serve as the basis for building intelligent systems, by specifying their cognitive capabilities and their components [46], [45], [25]. In this aspect, cognitive architectures should permit capabilities like understanding, recall, problem solving and learning [27].

Top-down designed cognitive architectures may be seen as personalised expert systems. Some authors group cognitive architectures according to the features of memory organisation and knowledge representation schemes into three groups: symbolic, emergent and hybrid [4], [5] (Table I).

A. Symbolic Architectures

Symbolic architectures model thought as the processing of symbols [22]. The symbols represent concepts and are processed by making use of a declarative knowledge about the symbols in the classical top-down approach [4], [5].

B. Emergent Architectures

The idea in emergent architectures is borrowed from adaptation in biological organisms, in which knowledge can be synthesised from interactions with the environment. The biological model is connectionist [13], whereas the symbolic approach is none-connectionist [22], [26]. Both architectures emerge from probabilistic evaluations of data, whose initial and ever continuing source is the environment.

Connectionist architectures model the mind as a network of interconnected processing nodes [4], [5]. For a given input, a specific group of nodes can be activated and this activation propagates through a network of intermediate nodes until an output is obtained [22], [43]. One of the main advantages of connectionist systems is that they can mimic autonomous learning.

C. Hybrid Architectures

Symbolic architectures have difficulties in constructing symbols from low-level information (stimuli) and in the processing of large amount of symbols, while they are good at achieving high-level cognitive functions [11]. Emergent architectures, on the other hand, have difficulty achieving higher level cognitive functions, while they are suitable for parallel processing of large number of low-level information (stimuli). Hybrid architectures combine both, such that the drawbacks of one are offset by the benefits of the other [22].

D. Consciousness

In addition to the above the three basic categories of cognitive abilities, self-consciousness is the mental ability that distinguishes human intelligence. It is the ability to perceive changes of own mental states [3]. However, current existing approaches of self-consciousness are rather humble attempts for modelling emotion or motivation.

Sometimes consciousness is used in the literature [17] to refer to the ability to perceive environmental changes that trigger high-level cognitive processes.

V. OTHER CLASSIFICATION SCHEMAS

In previous chapters we have discussed the three major design patterns of robotic agent architectures, mechatronic capabilities, behavioural capabilities and cognitive abilities. Out of the rich literature on classifications, we provide now a brief summary of some further common schemas (Table I).

A. Purpose

Cognitive Architectures can be divided into the following categories based on their purpose [17].

Architectures that model human cognition

These architectures are inspired by studies and experiments done on the functioning of the human brain. They aim at replicating the full functionality of the human brain, by combining different models developed for the different functionalities of the brain like memory, vision and learning. Examples of these architectures include ACT-R and Atlantis [17].

Architectures that intend general intelligence

These architectures do not limit themselves to representing functionalities in the exact form they are represented by the human brain. Their aim is to develop agents with general intelligence which can have potentially better problem solving capability than the human brain. Artificial General Intelligence is a field of study which aims at developing agents with such general capability [11], [49].

Architectures to develop intelligent control systems

These architectures focus more on the application of intelligence to specific real life problems than the development of general intelligence. They are used in control systems, to provide control beyond what conventional control systems would allow [38]. For instance, cognitive architectures for robust control of robots that behave intelligently in a team [1].

B. Degree of Perceived Intelligence and Capability

Based on the capability of the agents and the intelligence they exhibit, agents can be grouped into the following five categories [39]. This schema is analogous to the behavioural capabilities that was presented above (Fig 1).

Simple reflex agents

Simple reflex agents base their decisions on simple if-then rules. They do not make use of past experiences, when making their decisions. As a result, in complex environments, they have a tendency to get stuck by doing unfruitful actions continuously.

Model-based reflex agents

Model-based reflex agents have an internal description of their environment. Hence, they are able to work properly, even if a part of their environment is currently out of their view.

Goal-based agents

Like model-based agents, goal-based agents hold a model of the world. But, in addition, they hold a goal, which summarises all desirable outcomes they strive to achieve.

Utility-based agents

It is possible to achieve a goal in various ways, ie different resources may be required, to reach the same goal. In such a case, the optimum resource utilisation may be preferred. Thus, utility based agents strive to choose those actions that will lead to the goal in an optimised way, by assessing their resource utilisations.

Learning agents

Learning is useful to make agents adapt to new and changing environments. The performance element is equivalent to the whole agent discussed in the previous sections.

C. Emphasised Properties

Agents can be classified based on the properties that are emphasised into the following categories [36].

Collaborative Agents

The main properties that are exhibited by co-operative agents are autonomy and co-operation with other agents. Collaborative agents co-ordinate their activities with other agents through communication [21].

Interface Agents

The main properties that are exhibited by interface agents are autonomy and learning. Like collaborative agents, interface agents also involve collaboration. But, while the collaboration of collaborative agents is with other agents the collaboration of interface agents is with users.

Mobile Agents

Mobile agents are able to travel through a large area (virtual or physical) and come back after performing their tasks.

Information/Internet Agents

Information/Internet agents are software agents used for collecting large amount of information from various sources and for processing and organising of the information [12].

Reactive Software Agents

Reactive software agents are software agents which do not have an internal representation of their environment. Their actions are just a response to the present condition of their environment.

Hybrid Agents

Hybrid agents combine the ideas behind the gents we have seen so far to form a single agent that that solidifies their strengths and lessens their weaknesses.

Heterogeneous Agent Systems

Unlike hybrid agents that combine the underlying philosophies of different agents into a single agent, heterogeneous agents combine the agents as they are to form a system composed of multiple agents.

TABLE I. CLASSIFICATIONS OF ROBOTIC AGENT ARCHITECTURES BY DIFFERENT AUTHORS*

Criteria	Classification	Sample Architecture
Purpose [17]	Human Cognition	ACT-R and Atlantis
	General Intelligence	SOAR and BB1
	Intelligent Control System	4D/RCS and subsumption architecture
Cognitive Abilities [5]	Symbolic	SOAR [17], ACT-R, EPIC, ICARUS, SNePS [13]
	Emergent	HTM, DeSTIN, IBCA, NOMAD [13]
	Hybrid	CLARION, DUAL [44], LIDA [13]
	Consciousness	CLARION [45], PURR-PUSS and PSI theory [5]
Behavioural Patterns	Reactive	Subsumption architecture [34], [8]
	Proactive	Assistant agent for office settings, eg CALO [35]
	Deliberative	BDI agents [34], GRATE [8], HOMER [47]
	Interacting	MAGSY, MECCA [34]
	Autonomy	Agro robots [51], LAAS architecture [6]
	Computational Capabilities	Organisation-based MAS (OMAS) [31], AntEater & ElephantGun [42]
	Modularity	Adam [29]
	Operational Capabilities	Robot ontology [40]
	Hybrid	InterRaP, Touring Machines, Procedural Reasoning System (PRS), RCS, ATLANTIS [17]
Degree of Perceived Intelligence & Capability [39]	Simple Reflex	Vacuum cleaner robot that can sense current location and direction to continue the cleaning programme
	Model-Based Reflex	Vacuum cleaner robot that maintains a map of already cleaned room areas
	Goal-Based	Autonomous vehicle (Taxi) with the goal of reaching a given destination
	Utility-Based	Autonomous vehicle that reach its destination via an economic path
	Learning	Autonomous vehicle that learns to choose the right turns based on its previous experiences
Emphasised Properties [36]	Collaborative	MII (multi media information management agent) from BT Lab
	Interface	JASPER, internet information search agent that shares information among users
	Mobile	Sony's Magic Link PDA or Personal Intelligent Communicator (PIC)
	Information/Internet	Internet Softbot [12]
	Reactive	Subsumption architecture [8]
	Hybrid	Layered InteRRaP architecture [34]
	Heterogeneous	PACT (Palo Alto Collaborative Testbed) [36]
Pro-Activeness [15]	Pure Reaction	Subsumption architecture [8]
	Pure Planning	BDI (Belief,Desire,Intention) model
	Hybrid	JACK development environment
Adaptiveness [15]	Learning	Agents that use machine learning
	Subsumption Architecture	Subsumption architecture [8]
	Non-Adaptive	Mission critical agents
	Constraint Based	JACK development environment
Collaboration [15]	Communicative	Agents that communicate in KQML or FIPA [16]
	Non-Communicative	SWARM agent system
Veracity [15]	Truthful	Most agents in closed environments; eg JACK
	Untruthful	Most agents in open environments; eg FIPA JACK
Disposition [15]	Benevolent	Most agents in closed environments; eg JACK
	Self-Interested	Some agents in open environments; eg autonomous planes competing for landing on the same airport [4]
	Malevolent	Some agents in open environments; eg autonomous fighter planes from countries at war
Primary Mode of Interaction [34]	Autonomous	RAPs, NMRA, AuRA, ShopBot [14]
	Assistive	Tok, VET
	Multi-Agents	ECO model, Agent0/PLACA, MAGSY, GRATE [8]
Material State of Agent [34]	Hardware	RAPs, NMRA, AuRA
	Software	ShopBot [14]
Mobility [15]	Physically Mobile	Concordia agent, developed by Mitsubishi Electric ITA
	Logically Mobile	Web spider agent that visits and processes web pages by following hypertext links

*Different authors emphasise different abstractions, like agent, robot, behaviour or cognition.

D. Pro-Activeness

Agents can be classified based on their pro-activness, where their pro-activness falls under one of the following three categories [15].

Pure Reaction

Pure reaction involves basing one's responses only on the stimuli detected by sensors.

Pure Planning

Pure planning involves choosing of appropriate actions that will lead to achieving one's goals.

Hybrid

Hybrid agents aim at achieving superior performance by combining reactivity with planning.

E. Adaptiveness

Agents can be classified based on their adaptiveness into the following groups [15].

Learning

Learning agents are able to adapt their behaviours to suit their environment.

Subsumption

Agents with a subsumption architecture are layered agents, which can be made to adapt to their environment by adding new modules or layers that provide new functionality [9], [8]. Unlike learning agents, without the addition of new modules, the existing system cannot learn and adapt by itself.

Non-Adaptive

Non-adaptive agents never change their original behaviour which may be desirable in some situations.

Constraint Based

Constraint Based agents allow learning as long as it does not affect the execution of critical functions.

F. Collaboration

Agents can be classified into the following groups based on the form of their collaboration [15].

Communicative

Communicative agents are able to synchronise their activities with other agents through the exchange of messages.

Non-Communicative

Non-communicative agents do not have any direct communication with other agents, but can indirectly collaborate or compete with other agents as a result of the interaction with their environment.

G. Veracity

Agents can be classified into the following two groups based on their veracity [15].

Truthful

Truthful agents are agents whose actions and the information they provide can be trusted. Truthful agents usually occur in an environment where all the agents are from the same vendor.

Untruthful

Untruthful agents are agents whose actions and the information they provide cannot be trusted, since they actively work to deceive others.

H. Disposition

Agents may be classified by their disposition in to the following groups [15].

Benevolent

Benevolent agents are agents that are always willing to help other agents, by providing service or information, whenever they are requested [15], [33]. Benevolent agents usually have non-conflicting goals with the agents they offer help.

Self-Interested

Self-interested agents will provide help to other agents, if only they find it helpful to achieve their own goals [15]. Self-interested agents usually compete for resources with other agents in attempt to meet their goals.

Malevolent

Malevolent agents are agents which deliberately work to harm other agents [15]. Their actions are more intended for harming others than for achieving their own goals. As a result, they have destructive effect on the whole system.

I. Primary Mode of Interaction

Agents can be classified into the following groups based on the type of interaction with their environment [34].

Autonomous agents

Autonomous agents are agents that can realise their goals by themselves, without interacting with other agents or humans to get assistance [28]. Many autonomous control systems are considered as autonomous agents [34].

Assistive agents

Assistant agents are agents whose main interaction is with humans only.

Following six interesting classifications can be combined from the criteria material state and primary mode of interaction (Table I): autonomous hardware agents, autonomous software agents, hardware assistant agents, software assistant agents, hardware multi-agents and software multi-agents.

Multi-agents

Multi-agents are agents that interact with other agents and humans, with whom they collaborate and co-ordinate, in order to achieve their goals [34].

J. Material State of Agent

Robots with behavioural capabilities or cognitive abilities are referred to as physical agents, whereas software agents do not possess any mechatronic embodiment [34].

K. Mobility

Agents can be classified into the following groups based on mobility [15].

Physically Mobile

Physically mobile agents can change the machine they run on as they travel through a network.

Logically Mobile

Logically mobile agents run on one machine but can access remote resources using a network.

VI. A UNIFYING CLASSIFICATION SCHEMA

From the overview of the many classification schemas (Table I) one can observe various overlapping criteria and classifications. Out of these common properties [48], we suggest a classification that attempts to generalise all criteria, by considering further mechatronics.

A. Taxonomy

The suggested schema (Table II) is a summary of the classifications of agents and their cognitive architectures, which were provided in the previous section, by factoring out the common classification criteria used by different authors.

B. Discussion

Although embodied intelligence is long an accepted design approach for cognitive architectures, to the best of our knowledge, no classification schema was found that includes

TABLE **II. TAXONOMY OF ROBOTIC AGENT ARCHITECTURES**.

<table>
<tr><th>Criteria</th><th colspan="4">Classification Hierarchy*</th></tr>
<tr><td rowspan="3">Purpose</td><td colspan="4">Modelling human cognition</td></tr>
<tr><td colspan="4">General intelligence</td></tr>
<tr><td colspan="4">Developing intelligent control systems</td></tr>
<tr><td rowspan="3">Cognition</td><td>Symbolic</td><td colspan="3">Non-adaptive/subsumption</td></tr>
<tr><td>Emergent</td><td colspan="3">Learning/constraint based</td></tr>
<tr><td colspan="4">Hybrid</td></tr>
<tr><td rowspan="8">Behaviour</td><td colspan="4">Proactive</td></tr>
<tr><td>Deliberative</td><td colspan="3">Model based reflexive/goal based/utility based</td></tr>
<tr><td colspan="4">Reactive; Reflexive</td></tr>
<tr><td rowspan="3">Interaction mode</td><td rowspan="2">Multi-agents</td><td>Collaborative and truthful</td><td>Benevolent</td></tr>
<tr><td>Competitive and untruthful</td><td>Self-interested/malevolent</td></tr>
<tr><td colspan="3">User assistive</td></tr>
<tr><td colspan="4">Hybrid</td></tr>
<tr><td colspan="4">Heterogeneous</td></tr>
<tr><td rowspan="4">Mechatronics</td><td>Interaction type</td><td colspan="3">Sensor/actuator</td></tr>
<tr><td>Material state of object</td><td colspan="3">Wave/dynamic matter/static matter</td></tr>
<tr><td>Size of device</td><td colspan="3">Macro/micro/nano</td></tr>
<tr><td>Elementary environment</td><td colspan="3">Water/earth/gas/vacuum</td></tr>
<tr><td rowspan="2">Mobility</td><td>Mobile</td><td colspan="3">Physically/virtual</td></tr>
<tr><td colspan="4">Non mobile</td></tr>
</table>

* Hierarchy descending left-to-right

mechatronic capabilities [24], like in the taxonomy, we have proposed here.

The subsumption architecture [8] was probably one of the first attempts for an embodied AI model with a hybrid symbolic and emergent architecture. It was influential on many behavioural architectures, for learning lower-level behaviours from sense-act interactions. Meanwhile has been superseded by deep learning, which attempts to learn "deeper" into higher-level cognitive abilities.

Novel approaches for biologically inspired models for intelligence are expected from ongoing research results in neurological and brain research [7], [20], [32], [41].

VII. CONCLUSION

We have surveyed various classification schema for behavioural and cognitive architectures and revealed overlapping criteria they possess. Based on those common properties, we have proposed a generalised classification schema. Our analysis has involved mechatronic capabilities, in order for the new schema to comply with requirements of realistic systems towards embodied AI.

Our current effort is focused on developing a new cognitive architecture that hybridises approximate reasoning with learning ontologies [26].

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