Towards a Cloud-Based Architecture for 3D Object Comprehension in Cognitive Robotics

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***Abstract*—Cognitive robotics can take advantage of distributed, web-based information as a foundation for comprehending 3D objects in a 3D scanned world. The proposed CogOnto model makes possible grounding a cognitive computing system with sensor data gathered from diverse and heterogeneous sources, associated with humanly crafted symbolic descriptors. The system supports cognitive embodiment within the totality of an information ecology, and not just within the physical world where an individual robot, essentially a mobile peripheral device, is located. The informed system uses 3D objects as common denominators for shared world comprehension.**

Keywords-Cognitive Modelling; Eye Tracking/Steering; Human Robot Interaction; Knowledge base; Ontology.

I. INTRODUCTION

Field robotics technology has matured to the point where commercial robotics platforms are available for diverse applications, such as surveillance, sample and data collection, analysis and return, construction, agriculture and mining operations. Communications links with robots now have high data capacities. A consequence of these advances, however, is that human operators receive increasing amounts of data streamed from robots that they must perceptually and cognitively process, often in real time, in order to perform real-time tele-robotic tasks. This data input is often of an overwhelming volume and complexity. One approach to dealing with this task performance demand is to offload some or all of the required cognitive processing onto the robot platform itself. Hence *cognitive robotics* aims to develop intelligent software capable of performing highly automated cognitive task performance by robots in order to optimize their use and take best advantage of the latest hardware developments. Artificial Intelligence (AI) has long sought solutions for making robots more intelligent, with rather limited success.

The formation and use of representations, and the possibility of making representations meaningful, is a key attribute of intelligence, and is one of the areas where AI has met challenges due to the human authorship of representations in traditional AI systems; the representations are too abstract to be grounded for the technical artifact, do not change with their contexts, require human interpretation to provide their meaning, and have arbitrary bounds [1].

Grounding the formation of symbolic representations in dynamic and embedded processes as biological systems do provides one approach to trying to avoid these issues in knowledge representation. However, the increasing availability of extensive broadband communications networks, high capacity computer memory and processing services, and extensive on-line data, suggests an alternative approach to symbol grounding and embedded cognition. This is by the use of repositories of previously captured sensor data together with real-time sensor data that have labels and semantic annotations supporting their discovery and reuse in AI systems. A cognitive robotics system realized on this basis can have the following features:

- Agency can be nested, where *a robot* consists minimally of a hardware platform.
- The on-board processing ability of a robot can scale, from low level interfaces for sensor transmission and command reception, through increasing levels of on-board autonomy, to full autonomous operation [2].
- Intelligence in the system does not need to be physically encapsulated or localized.
- Intelligent agency can be mapped across one or more robot platforms and hardware processing networks, with cognitive processing that is partially or wholly cloud-based.
- An intelligent agent can use the cloud-based memory of past perceptions of other robotic and human sensory data as a technical analog of human episodic memory.
- All ongoing and past sensor streams, decision processes and generated actions (i.e. the ‘experiences’) of agents can be stored for analysis and application in ongoing and future task performance.
- The scope of an agent can be scaled in proportion to the task that it is performing and the environment in which the task is performed.

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Robotics research is beginning to explore ideas like these in a number of scenarios [3]. In this paper, we focus on the use of robotic 3D object perception and propose the use of a cloud-based infrastructure to implement a machine vision paradigm inspired by Marr's theory [4] of visual cognition. We also propose a method of using 3D simulation integrated with this perceptual approach. The derivation of 3D model data from perception provides world state information as input to an ongoing world simulation. The simulation provides predictions about future states. Those predictions facilitate rapid processing in future perception. The comparison of predicted states with perceived states also provides foundations for tuning the simulation and its parameters, that can also be represented declaratively to support higher level reasoning. The proposed *CogOnto model* described below stores the process and object(s) information in a knowledge system that can guide the robot in physical collaboration, manipulation and navigation.

The structure of the paper brings you as a reader from a 'high level architecture' to '3D visual processing' and thereafter to 'intelligent action in a structured world'. The actual contribution of this paper is presented in the section 'proposed model', followed by 'integrating semantic web concepts, resources, and technologies to the final summary.

II. HIGH LEVEL ARCHITECTURE

When the robot is operating in the physical world it may be controlled by a cognitive agent residing off-board, see Fig. 1.

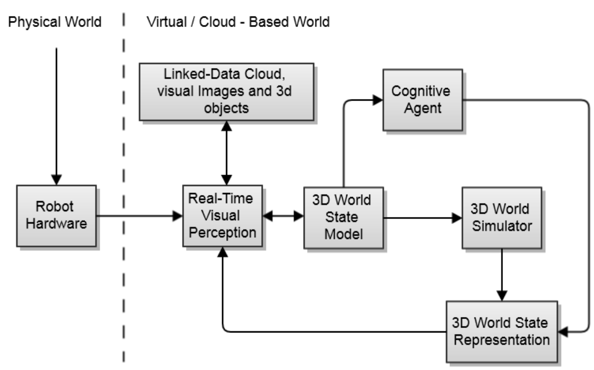

Figure 1. Robot hardware assisted by the cognitive agent where real time 3D object perception and recognition are supported by the 3D virtual world and knowledge cloud.

If the robot shall observe and manipulate a 3D object, it must have real time perception, comprehension and memory recall so that the robot knows how to execute the manipulation task(s) via motor action. The linked data cloud is operatively called to match already stored 3D object information parallel to real time 3D object extraction from the scanned physical world: this is the recognition phase. The 3D world state model constitutes a virtual world derived from a scanned *volume of view* where objects and object motions are captured, digitized and recorded. The recorded information is fed into memory and can be used for simulation scenarios and prediction of scenario events. Notice in relation to 'first order predicate calculus' [5] that 3D objects here are both subjects and objects, while adjectives and verbs are predicates.

III. 3D VISUAL PROCESSING

The ability to scan a real world environment makes it possible to extract digital information about the physical world and how it functions. Three dimensional perception is a key technology for robotics applications where obstacle detection, mapping and localization are core capabilities for operating in unstructured environments. Laser scanning creates a surface point cloud of a 3D physical environment [6] making it possible to map any environment in a rather short time (the Leaning Tower of Pisa was scanned in 20 minutes). This technology can be used in a robotic intelligence system for Simultaneous Localization Mapping (SLAM) and higher level reasoning regarding location and position. However, object recognition and manipulation requires deriving 3D object information from the overall point cloud and building cognitive models with task reasoning for using object and scene data in real time.

Object extraction [7][8][9] makes it possible to know what a robot is looking at, supporting manipulation or collection actions. This can be achieved by an Environmental Scanning-Object Extraction (ES-OE) engine. For human-robot collaboration, a robot can be enabled to use deictic visual references from human gaze by integrating an eye tracker with the ES-OE engine.

A. Background

In a previous work [10], a 3D simulation engine was integrated with an eye tracker. The integrated system allows the human point of gaze on 3D objects within a 3D digital world projected onto a computer screen to be tracked automatically. This development made it possible to log gaze in various task-related environments in a simulated world. From a Human Factor's perspective, the simulation and human observation can be investigated, including collaborative actions performed by groups with various workloads, stressors and decisions. There have been several studies made using the technological framework with different stimuli [11][12][13], but no substantial theoretical framework has been developed in relation to this object-based approach *per se*. A bottleneck in relation to this visual approach has been that 2D image, film and visual stimuli have not met the requirements for incorporating a knowledge-based approach for dynamic 3D worlds, whether the real physical world or a digitized 3D world. The object approach needs to address how both modeled and real world objects can be perceived and manipulated [14] by a robot, allowing the system to sense, think and act in real time: the computer needs to understand how to define an object and how to ontologically and semantically make sense out of such an object in a dynamic spatial world.

1) 3D objects in a 3D world

In [10], a simulation engine integrated with an eye tracker took a gaze fixation (x and y screen coordinates) and ray

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casted/traced from that position onto the underlying 3D virtual object's collision box, a volume corresponding with the shape of a virtual object as recognized and processed by a physics engine that is also used to designate objects by interface devices, like a mouse. This made it possible to track gazed objects in real time every 17 ms (using a 60Hz eye tracker). The same principle can be used in a physical world context where an ES-OE engine could be integrated with eye tracking glasses to allow a computational system to know what object a person wearing the glasses is looking at.

2) *Structuring a noisy world*

The 3D world scenario, simulated or physically real, constitutes an event or scene. A scenario includes objects that are instances of their classes. A class could be something like a *CarClass*, *HumanClass*, *FlowerClass*, etc.

In a constrained world, we can name all objects beforehand so when they are logged we know what they are and what position (x, y, z, θ_1, θ_2, θ_3) they are in. In an unconstrained environment that is scanned and has extracted objects, we must also have a capability to know what the objects are and to be able to classify them. A cloud-based approach of the kind proposed in this paper presents a middle ground, being more open than a highly constrained environment, but still being limited to objects of types that are represented and labeled within the cloud.

IV. INTELLIGENT ACTION IN A STRUCTURED WORLD

Knowledge by definition is "1. Facts, information, and skills acquired through experience or education; the theoretical or practical understanding of a subject and 2. Awareness or familiarity gained by experience of a fact or situation." [15]. To gain an understanding of how robots might learn and operate on knowledge, we have looked at several established models that can fit within an initial architecture that enhances these established models by the ingestion of information from the web. Our overall aim is to build a computational comprehension system for 3D object information, assisted by a hybrid computational ontology (i.e., combining several existing and new ontologies).

A. *Existing Models*

Extensive effort has been put into the task of understanding and attempting to re-create/simulate the processes by which a human being thinks. Using the underlying assumption that intelligence is wholly "the simple accrual and tuning of many small units of knowledge" [16], production-based models of cognition have had success in displaying human-like performance on a number of tasks (e.g., visual search [17] and natural language processing [18]). While there are debates regarding the similarity of what humans actually do to what we have achieved using the above assumption [19], there is little doubt that such systems can produce intelligent-seeming behavior, that can facilitate the development of vitally useful control structures in the field of robotics and computational intelligence [18].

One of the most influential models of human cognition is the ACT-R, or "Adaptive Character of Thought – Rational" model [16], developed over many years by John Anderson, who was a student of the seminal Cognitive Scientist Alan Newell (1927-1992). Anderson's model is a hybrid symbolic/sub-symbolic system that incorporates various "modules" that are deemed necessary for rational behavior, and are thought to have biological correlates. These include the modules *Declarative* (manages creation, storage and activation of memory "chunks"), *Procedural* (stores and executes productions based on expected utility), *Intentional/Imaginal* (goal formulation for directed behavior), and *Visual (2D)/Audio* (theoretically plausible implementation of visual and auditory perception), see Fig. 2. An internal pattern-matching function searches for a production that matches the current state of the buffers.

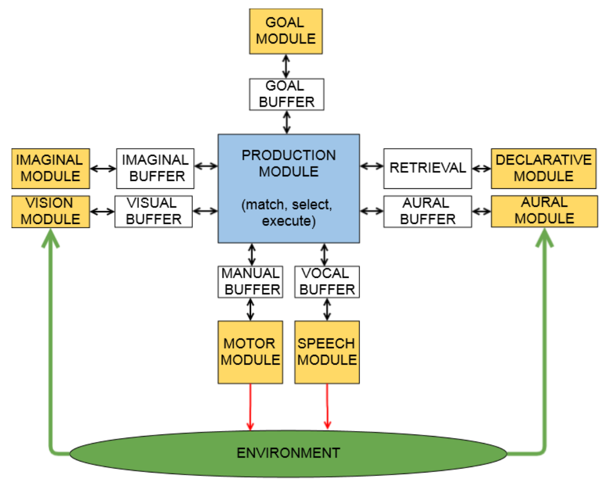

Figure 2. A schematic representation of the canonical ACT-R cognitive model.

ACT-R is formed as a knowledge model where the "chunks" are the elements of declarative knowledge in the ACT-R theory and are used to communicate information between modules through the buffers. A chunk is defined by its chunk type, that is described by its slots (here compared with properties), see table 1. Chunk types can be organized as a hierarchy of parent (SuperType)-child (SubType) relationships. The subtype will inherit all of the slots (properties) of the parent node(s).

Other models that take a similar symbolic approach to model human cognition include Soar [20], EPIC [21], CLARION [22], and others (for a detailed review see [23]). While these have been successful to varying degrees at modeling specific human cognitive task(s) performance, it is becoming evident that such models are intrinsically limited by their disconnections from the real world in which humans (or robots) operate. A production based system is only as adaptive as its rule set allows given the inputs provided to it, that have generally been limited to "screen as eye" and "keyboard/mouse as hands" mappings. A new wave of thought surrounding the development of cognitive models is embracing the need for "embodied" cognition, improving the ability of the system to sense and act. One example of this is the ACT-R/E framework, used as an operating system for

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mobile robotics developed by the American Naval Research Lab [24], depicted in Fig. 3.

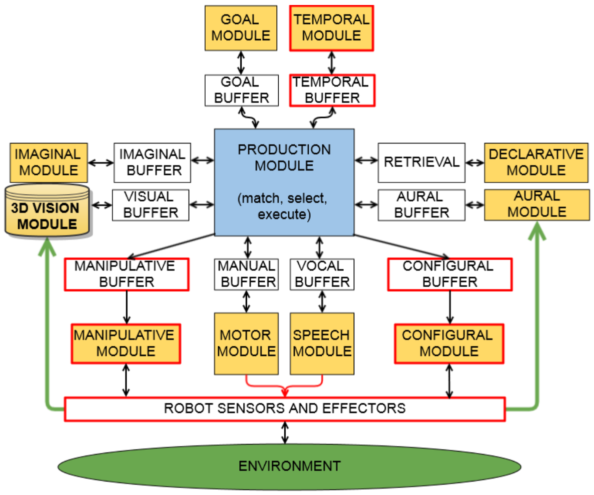

Figure 3. The "embodied" (Visual 3D) modifications introduced by Trafton et al. 2012. Additions in the ACT-R/E are highlighted in red.

The Object-Attribute-Relation (OAR) model of Wang, 2007 [25], specifies the elements of a cognitive model in the fashion of an ontology, the logical model of memory. In an attempt to formally describe the mechanism of human Long Term Memory (LTM), which he states is the "foundation of all forms of natural intelligence" (p. 66), Wang decomposes the construct into three elemental components – Objects, Attributes and Relations. This OAR model allows the computational specification of the human LTM formation and storage process, and is put forth as having sufficient explanatory power as to describe the "mental process and cognitive mechanisms of learning and knowledge representation" (p.72). This model has a strong parallel with the specification of knowledge in information processing Ontologies. This parallel is direct, as described by the relations given in Table I.

TABLE I. COMPARISON OF MODEL TYPE CONSTRUCTS

OAR Model	Ontology Components	ACT-R ACT-R/E
Object(s) Attribute(s) Relation(s)	Class(es) Propert(ies) Relationship(s)	Chunk Type(s) Chunk Slot(s) Function(s)

A critical issue for any of these kinds of models is the relationship of their constructs to the environments in which they are expected to provide foundations for action. The core notion of *embodiment* is to provide the heretofore functionally "disembodied" computational model with sensors and effectors that allow its direct interaction with the physical world. In such a way, the inherent limitation of human-defined input may be overcome. In addition to physical sensory perception and manipulative ability, a human may have access to a detailed semantic understanding of the surrounding world. In the quest to produce a non-human intelligent actor within a physical space, we must provide the actor with an understanding of underlying structures, i.e. specific denotations in the physical world.

V. PROPOSED MODEL

In the CogOnto model, we propose a further augmentation of the cognitive models discussed above, providing the robot with detailed 3D schematic representations of objects that it encounters in real time, supported via task models, knowledge models and ontologies.

The CogOnto model is composed of five parts $\triangleq$ $<S_i,C_i,A_i,O_i,R_i>$, where $i = 1..N$, and where S_i is a finite set of situations, C_i is a finite set of classes, A_i is a finite set of attributes for characterizing a class, O_i is a finite set of objects in a class, and R_i is a finite set of relationships among the objects. In the CogOnto model (Fig. 4), we consider the following features [26][27]:

- Situation: represents an interactive (i.e. dynamic) real world scenario.
- ConceptNet: is a network of class-to-class relationships applicable in a given situation.
- ObjectNet: an object is an instance of a class. ObjectNet is a network of object-to-object relationships.
- AttributeNet: is a network between properties of classes and objects.
- Relation: is a function associating concepts, classes, objects and attributes; e.g. a *robot* is *part-of* an *Intelligent Agent (IA)*, were the "part-of" relation connects two concepts. The relations (associations) may be modeled or created by an autonomous learning process.

These constructs are not defined in detail here, but unlike the other models are not limited to textual/linguistic meanings. The CogOnto model illustrated in Fig. 4 has four major functional elements that share information: 1) the ES-OE engine, 2) the eye tracking system interconnected with the ES-OE engine, 3) the OAR model functioning as the basis of the Cognitive System, and 4) the knowledge cloud, including external resources such as WordNet or Cyc. The latter is also called the Linked Open Data and may be used to illustrate the intelligent process for sharing and exposing information in machine readable form by using uniform resource identifiers based on Berners-Lee's [27][29] principles. These principles enable data communication guiding perception from procedural memory.

The knowledge system of the CogOnto model can be perceived as a storage system that accesses real world object information and external semantic resource information via the existing knowledge cloud [29].

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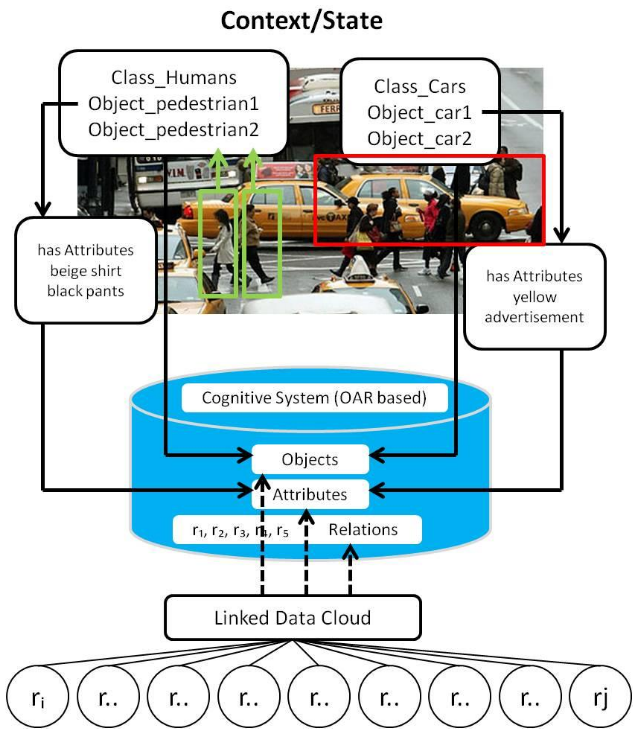

Figure 4. An illustration of the CogOnto model and its operative states.

The knowledge system represents the integration of formal symbolic and free text descriptors of an object.

VI. INTEGRATING SEMANTIC WEB CONCEPTS, TECHNOLOGIES AND RESOURCES

CogOnto integrates its own knowledge resources with external resources accessible via the web. For example, WordNet is a lexical database where nouns, verbs, adjectives and adverbs are grouped into sets of cognitive synonyms (synsets). To recall an object, the 'synsets (WordNet 2.1)' [30] and the W3C [31] standard can be used at a text level, to describe what an object is when it is text-labeled. Ontologies can be expressed by using Semantic Web tools, e.g. Web Ontology Language (OWL) [32] and the Resource description framework Schema (RDFS) [33].

The OAR model, with its Object, Attribute and Relation parts, and the ontological framework, containing Class/Instance, Relationship and Properties, can be inter-mapped so the object world can be comprehended using existing resources and using the 3D information represented internally within an object model. The 3D object's internal structure and shape can either be structured as Free Form Geometry (FFG) with surfaces and curves, or as Polygonal Geometry (PG) with points, lines and faces. The objects can be extracted and exported into different file formats, such as e.g. .obj files, .stl files. The .stl file format is a triangular representation of a 3D object, where each triangle is uniquely defined by its normal and three points representing its vertices. The format is native to the stereolithography Computer Aided Design (CAD) software created by 3D Systems (in this kind of format it is also possible to print the object out from a 3D printing machine).

The 3D object file contains different layers cognitively (form, volume, size, other descriptive attributes, etc.), supporting our senses and perception operating in parallel when performing allocated manipulation tasks. A human looking at an object can relate to the object both on a denotative- and on a connotative level. The denotative level is understood as a pure noun level without any cultural associations, nor any emotional or associative signifiers to the object, it is purely instrumental. The connotative layer is, on the other hand, the level of cultural and personal associations attached to an object with experience over time. Geometrical information within the 3D object can be represented using the X3D XML-based file format, an ISO standard for representing 3D computer graphics.

VII. CONCLUSION AND FUTURE WORK

The CogOnto model with support from the technological implementation of the eye tracker system with the ES-OE engine can represent cognitive relations that can be processed by a robot operating in a spatial world [34].

Formal knowledge structures within CogOnto face similar challenges to other knowledge representation formalisms, and this paper has shown isomorphism with a number of examples. However, the primary advance proposed is to use cloud-based resources that are not limited to formal representations to enhance the robustness of knowledge processing by the integration of similarity-based search. Those cloud-based resources may use text and images. But more interesting extensions for future work include new forms of cloud content, such as multi-spectral images, point clouds and behavior tracks. The main ongoing research challenge is to provide suitable similarity metrics for these data forms, integrating search results with formal structures, and developing methods for integrating them in unified search, or meta-search, results.

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