Ontology-Based Cognitive System for Contextual Reasoning in Robot Architectures

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Abstract

We present a hybrid system for reasoning over contextual and spatial elements of environments. The system, designed for deployment in robot architectures, leverages a knowledge base framework for common-sense reasoning through the integration with the symbolic and sub-symbolic structures of a cognitive architecture. Methodological and functional aspects are illustrated, together with an overview of the results obtained in a synthetic simulation experiment.

Introduction

Envisioning the outcomes of an action on the basis of current experiences and pertinent memories is one of the primary competencies of the mind: this predictive capability (Kurzweil, 2012) unfolds when perceptions and knowledge representations come together in a comprehensive process of pattern recognition, prompting actions under "context-awareness". In particular, humans constantly need to sort out sensory cues when dealing with their surroundings: they can decide to approach targets, stop or move away from threats, dodge obstacles or manipulate useful objects, constantly adapting to mutable environmental conditions to preserve their life and accomplish their goals. Though no ultimate explanation has been given of how humans can generalize over perceptual contents, create mental representations and reason over them to guide the pattern recognition process, studies in Cognitive Science have produced some insight. For instance, according to (Tversky, 1977) & (Biederman, 1987), similar objects have a high degree of overlapping components (scissors and knives, doors and windows, etc.), while spatial proximity depends on circumstantial conditions (nearby a hospital, there are probably a parking lot and a heliport, proper road signs, etc.). These generic principles encode just a small fraction of the amount of knowledge that humans commonly exploit in accomplishing their everyday tasks. Moreover, this knowledge is not available *a priori*: it is learned by accumulation of experience. In this sense, the relationship between perceptual and knowledge structures is a key element of the high-level cognitive mechanisms that determine intelligent behavior in the environment, and that ultimately can be replicated by robotic architectures. The main challenge, in this regard, is represented by the embodiment of cognitive-based systems in robotic architectures: if the design of intelligent systems for navigation an object recognition traces back to the dawn of robotics (Moravec, 1988), the novelty of the cognitive approach is to look at human solutions, enriching traditional AI algorithms with a "bounded rationality" approach (Simon, 1991), as shown by recent work in the field (Cassimatis, Trafton, Bugajska, & Schultz, 2004; Kelly & Avery, 2010; Trafton, Hiatt, Harrison, & Khemlani, 2012; Hawes & Klenk, 2012; Kurup & Lebiere, 2012).

This paper is situated in this research framework: we present, in particular, an ontology-based cognitive system for identifying and recognizing building configurations on the basis of geometrical features of walls and contextual features of the surroundings. In the paradigmatic scenario, a robot navigates through an outdoor environment carrying out tactical behaviors typically issued by soldiers (e.g. "screen the backdoor of a building"): the hybrid system, in this respect, aims at supporting navigation and planning routines with high-level pattern recognition, mimicking the human capabilities of discriminating signals from the environment and acting accordingly.

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Combining Ontologies and Cognitive Architectures in a Hybrid Intelligent System

In this section we briefly introduce the two components of the above-mentioned hybrid system, namely the ACT-R architecture (Anderson, 2007) and the SCONE Knowledge Base System (Fahlman, 2006).

ACT-R Cognitive Architecture

Cognitive architectures attempt to capture at the computational level the invariant mechanisms of human cognition, including those underlying the functions of control, learning, memory, adaptivity, perception, decision-making, and action. ACT-R (Anderson & Lebiere, 1998) is a modular architecture including perceptual, motor and declarative memory components, synchronized by a procedural module through limited capacity buffers. The declarative memory module (DM) plays an important role in the ACT-R system. At the symbolic level, ACT-R agents perform two major operations on DM: 1) accumulating knowledge "chunks" learned from internal operations or from interacting with objects and other agents populating the environment and 2) retrieving chunks that provide needed information. ACT-R distinguishes 'declarative knowledge' from 'procedural knowledge', the latter being conceived as a set of procedures (production rules or "productions") which coordinate information processing between its various modules (Anderson & Lebiere, 1998): accordingly, agents accomplish their goals on the basis of declarative representations elaborated through procedural steps (in the form of *if-then* clauses). This dissociation between declarative and procedural knowledge is grounded in experimental cognitive psychology; major studies in cognitive neuroscience also indicate a specific role of the hippocampus in "forming permanent declarative memories" and of the basal ganglia in production processes - see (Anderson, 2007), pp. 96-99, for a general mapping of ACT-R modules and buffers to brain areas and (Stocco, Lebiere, & Anderson, 2010) for a detailed neural model of the basal ganglia's role in controlling information flow between cortical regions). ACT-R performs cognitive tasks by combining sub-symbolic computations and symbolic knowledge structures: in these regards two core mechanisms are important in the context of this paper: *i) partial matching,* the probability of association between two distinct declarative knowledge chunks, computed on the basis of suitable similarity measures; *ii) spreading of activation*, the phenomenon by which a chunk distributionally activates related chunk patterns.

Expanding ACT-R with SCONE

In general, ACT-R models only employ as much knowledge as required to perform well-defined cognitive tasks. By and large, they can be seen as "monadic" agents, whose knowledge bases are limited, partially reusable and sporadically portable across experimental conditions. On the contrary, in order to replicate high-level contextual reasoning and pattern recognition in humans, large amount of common-sense knowledge should be available to ACT-R: to overcome these limitations, we propose to equip ACT-R with a specific module for processing *ontologies*, i.e. semantic specifications of a given domain or application (Guarino, 1998), which are generally used in combination with inference engines for deductive reasoning. Since the ACT-R declarative module supports a relatively coarse-grained semantics based on slot-value pairs, and the procedural system is not optimal to effectively manage complex logical constructs, a specific extension is needed to make ACT-R suitable to fulfill knowledge-intensive cognitive tasks like context-driven spatial reasoning. Accordingly, we engineered an extra module as a bridging component between the cognitive architecture and an external knowledge-base system KBS), SCONE (Fahlman, 2006). SCONE is intended for use as a component in many different software applications: it provides a framework to represent and reason over symbolic common-sense knowledge. Unlike most diffuse KBS, SCONE is not based on Description Logics (Staab & Studer, 2004): its inference engine adopts marker-passing algorithms (Fahlman, 2006), originally designed for massive parallel computing, to perform fast queries at the price of losing logical completeness and decidability. In particular, SCONE represents knowledge as a *semantic network* whose nodes are locally weighted (*marked*) and associated to arcs (*wires*) in order to optimize basic reasoning tasks (e.g. class membership, transitivity and inheritance of properties, etc.)[1]. The philosophy that inspired SCONE is straightforward: from vision to speech, humans exploit the brain's massive parallelism to fulfill all pattern recognition tasks; if we want to deal with the large amount of knowledge required in common-sense reasoning, we need to rely on a mechanism that is fast and effective enough to simulate parallel search. Shortcomings are not an issue here since humans are not perfect inference engines either, as also claimed by the "bounded rationality" principle (see previous section). Accordingly, SCONE implementation of marker-passing algorithms aims at simulating a pseudo-parallel search by assigning specific marker bits to each knowledge unit. For example, if we want to query an ontology of automotive body design

[1] In general, a *wire* can be conceived as a binary relation whose domain and range are referred to, respectively, as 'A-node' and 'B-node'.

to get all the parts of a car body, SCONE would assign a marker M1 to the 'A-node' *Car* and search for all the statements in the knowledge base where M1 is the A-wire (domain) of the relation *part of*, returning all the classes in the range of the relation (also called `B-nodes'). SCONE would finally assign the marker bit M2 to all B-nodes, also retrieving all the inherited subclasses (e.g. *window section*, *rear panel*, *hood vent*, etc.). The implementation of ontologies with SCONE allows for effective formal representation and automatic inferencing of knowledge structures.

A Cognitive System for Building Prediction

General Aspects

We present here a hybrid model for recognition of buildings on the basis of constituent walls and contextual awareness of the spatial surroundings. The model has been built in the framework of the hybrid cognitive system constituted by ACT-R cognitive architecture and SCONE KBS and evaluated in a thorough synthetic simulation. The robotic architecture also includes a component called the "World Model," which effectively serves as an object store for elements identified by the robot's perceptual systems. In the application scenario, as long as the robot *perceives* building components such as walls, doors, windows etc. and the World Model is populated with the resulting information (which plays the role of central information repository for all the other components), ACT-R is used to process the incremental data, and update the shape of a given building according to progressive predictions. In this way, the robot has access to incremental "projections" of the geometry of a building, which can then be synchronized with the navigation planning process. For the sake of simplicity, in the examples we'll go through below direct communication between semantic perception modules and the hybrid cognitive system is assumed, bypassing the World Model framework.

Figure 1. Aerial view of the FTIF test facility.

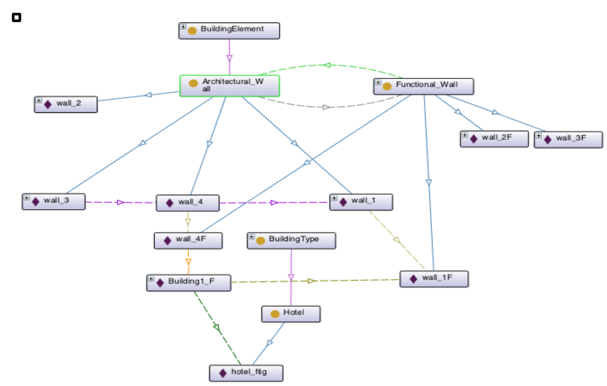

Figure 2. Example of distinction between functional and architectural features of buildings.

Modular Ontologies for the representation of space

This section outlines the suite of spatial ontologies encoded in SCONE and used by the hybrid system to perform high-level reasoning. Despite the extensive literature on using spatial reasoning in information systems (Bateman & Farrar, 2005), to our knowledge there has been just one attempt to apply spatial ontologies to tactical behaviors executed by unmanned ground vehicles (BouSaba, Esterline, Homaifar, & Fatehi, 2008). In this respect, our approach aims at making a step further with respect to the state of the art, by actually *engineering* and *testing* spatial ontologies into a full-fledged cognitively-driven robotic system. For this purpose we have developed HORUS (Hybrid Ontology for the Representation of Unified Space), a comprehensive ontology of buildings created by mapping primitive concepts and relations extracted from a library of spatial ontologies to the World Model's semantic data types. HORUS is essentially grounded in two open-source ontologies: DOLCE-Lite, which includes basic spatial concepts and related properties (part, region, extension etc., see Borgo & Masolo, 2009) and RCC-Ontology, including primitive topological relations like "connection", "overlap", etc. (Kutz, Lücke, & Mossakowski, 2008).

HORUS has the twofold purpose of 1) providing machine-readable semantic specifications of the World Model datatypes and 2) structuring and populating the declarative knowledge of an ACT-R model for building prediction. Regarding point 1), we have started mapping the spatial representation of buildings and walls of a test site (Fort Indiantown Gap – FTIG – see Figure 1 for an aerial view of the facility) with geometrical and morphological properties adopted by the navigation planner of the RCTA architecture. Integration was engineered by using the suite of different spatial ontologies mentioned before. In this sense, HORUS exemplifies a modular approach, where conceptual qualitative and quantitative spatial properties are considered as separate information layers from the representational and inferential viewpoint, though being incorporated into a common ontological infrastructure (a quantitative ontological layer for the representation of discrete measures is also available, though in this paper we are mainly focusing on qualitative spatial reasoning).

Figure 2 illustrates the main distinction between architectural and functional features of walls and buildings, where the former are internally constrained by metric and construction characteristics (quantitative layer), while the latter refer to the spatial regions defining the area of operations of the mobile robot. In particular, we can notice that the functional *building1_F*, which realizes *hotel_FTIG* requirements, is comprised – among the others – of functional *wall_1F*, whose architectural equivalent *wall_1* is externally connected to *wall_4*. Concerning point 2), HORUS has been implemented in the SCONE KBS, serving as a knowledge base and inference engine of the ACT-R cognitive model for building prediction: in particular, chunk types for walls, building patterns, surrounding objects etc., have been designed on the basis of the conceptual specifications of HORUS and properly rendered into ACT-R declarative semantic chunks. The mechanism of building pattern recognition based on HORUS leverages a combination of general common-sense knowledge and specific topological features of given test sites. In the medium term, we are planning to rely on diversified use cases from a realistic FTIG-based scenario to implement and assess cognitive learning mechanism for recognizing previously unseen buildings, eventually storing new emergent patterns in HORUS as the result of a cognitively-based knowledge acquisition process.

Functional model of building prediction

The diagram in Figure 3 shows at the functional level how the cognitive system elaborates perceptual information. In particular, the human-like capability of recognizing complex objects – in our specific case buildings – on the basis of component parts and relative spatial properties is emulated by the pattern matching mechanisms realized by the ACT-R cognitive architecture synchronized with SCONE KBS. The ACT-R model encodes perceptual inputs in declarative memory, associating them to pre-defined chunk types, the most relevant ones being “Wall” and “Building”. The chunk type “Wall” contains metric information represented by appropriate slots, e.g. height, width and orientation. The chunk type “Building” denotes a known configuration of the building via a set of specific walls, some invariant structures of the surroundings like a asphalted or graveled terrains, road signs, obstacles[2]. After the encoding phase, which in the real-world scenario is iterated as long as the robot moves and perceives the environment, the actual procedures of recognition are triggered: in particular, *partial matching* is used to compare input walls to the set of walls that constitute building patterns. This comparison is driven by metric characteristics: similarity is defined with respect to the difference between the dimensions of a perceived wall and the dimensions stored in declarative memory. The model is currently able to compute a composite measure based on heights and widths: the smaller the difference, the more likely the perceived wall belongs to the building pattern containing a wall with the same spatial characteristics. But in reality, wall size is not sufficient to discriminate which is the best matching building: for instance, hotels and hospitals may look akin in terms of shape and wall composition, despite having completely different purposes. In these regards, it may be beneficial for the recognition procedures to also process distinctive features of the building surroundings, like signs, benches, parking lots, heliports, sidewalks, gravel ground etc. In the example illustrated in figure 3, few walls are detected by the robot vision systems, together with a car and a sidewalk. In order to enhance the overall recognition/prediction, the ACT-R model evokes the SCONE KBS through the dedicated module, querying HORUS about whether the collected perceptual contents instantiate any significant ontological relationship. In particular, tests are made to check for 1) *equivalence*, the fact that two entities are of the same kind (e.g. car, sedan) 2) *part-of*, the fact that an entity is part of another (wheel, car), and 3) *feature*, defined as a special “parasitic” part that exists in virtue of the host object (e.g. a bump of a road, a hole in a shoe, the bottom of the table), and – in our context – all the features of a building, e.g. a window in the wall, the grass porch of a house, the sidewalk in front of the entrance door, etc. – (Simons, 2000; Van Inwagen, 1995). As depicted in Figure 3, the query trivially fails to retrieve relevant results for the first two tests (NIL value is returned), whereas the fact that the sidewalk is a feature of the detected wall W_1 is confirmed as being a true statement in the ontology HORUS – which means that it has been included as an assertion or ‘A-Box’ in the ontology (Sowa, 1984). In our system, a validation

[2] These configurations are harvested from a database containing topological and morphological information about the given test site.

of perceptual cues by background knowledge prompts the ACT-R sub-symbolic mechanisms of *spreading of activation*, so that the related chunks (in this example only "sidewalk") are used to boost the activation of the "consistent" building pattern chunks, penalizing the inconsistent ones. ACT-R chunk activation is calculated by the following equation:

$$A_i = \ln \sum_j t_j^{-d} + \sum_k W_k S_{ki} + \sum_l MP_l Sim_{li} + N(0,\sigma)$$

On the basis of the first term, the more recently and frequently a chunk i has been retrieved, the higher the activation and the chances of being retrieved (t_j is the time elapsed since the j^{th} reference to chunk i and d represents the memory decay rate). In our scenario this would correspond to the priority accounted to more recent perceived walls over older visual cues. In the second term of the equation, the contextual spreading activation of a chunk i is set by the attentional weight W_k, given the element k and the strength of association S_{ki} between k and the i (the more "consistent" k and i are, the higher S_{ki}). The third term states that, under partial matching, ACT-R can retrieve the chunk that matches the retrieval constraints to the greatest degree, combining the similarity Sim_{li} between l and i (a negative score that is assigned to discriminate the 'distance' between two terms) with the scaling mismatch penalty MP (in our case similarity between walls is based on metric dimensions). The final factor adds a random component to the retrieval process by including Gaussian noise to make retrieval probabilistic.

We've previously used the quotation marks to highlight that the notion of "consistence" into play here goes beyond pure logical formalisms, involving cognitive plausibility weighted through stochastic mechanisms: this is a noteworthy aspect of using a non-algorithmic cognitive approach to problem solving, where reasonableness of results replaces optimality, and shows how probabilistic reasoning and logic-based frameworks can be combined to perform knowledge-intensive tasks. The unified output of the reasoning procedures can be expressed by a probability distribution over the activated building patterns, where the most active pattern is "Hotel" in the example provided by Figure 3. In the next section we present in more details how probabilities of activations are distributed over building patterns across different testing conditions.

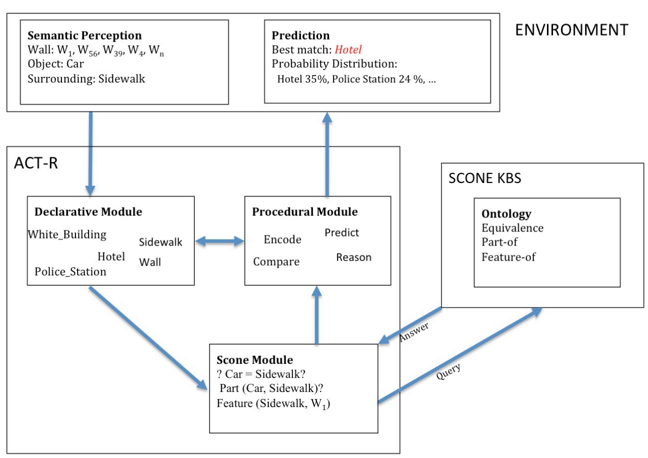

Figure 3 Functional Diagram of the Hybrid Cognitive System

Evaluation

The current capabilities of the hybrid cognitive system have been analyzed in a synthetic simulation designed to cover alternate perceptual conditions: in this respect, the test that we conducted assumes that the semantic perception modules can classify objects in the field of view without ambiguity or degradedness.

The evaluation set consists of the 14 different buildings located in the FTIG test site, including "restaurant", "church", "fire station", "crypt", "ops storage", "police station", "mayor's mansion", etc.: despite the distinctive semantic labels, the *inherent differences* within buildings mainly concern the metric level, in particular the height and width of constituent walls. Consequently, we designed differential experimental settings with the purpose of gauging the effect of variable levels of complexity in the prediction process, hypothesizing that the robot progressively perceives one wall, two walls, three walls and four walls. This sequence of visual inputs denotes incremental levels of completeness with respect to predefined building patterns, although – as we'll see in the experiments – permutations of walls from different building patterns are also explored. In addition to metric similarities, we tested the extent to which, validating *extrinsic differences* within buildings by means of the HORUS ontology increases the probability of retrieving the correct pattern. In compliance with this premise, the ontology reflects the constraint that each building can be associated to no more than two relevant features, spanning from diverse types of terrain (e.g., "grass", "asphalt", "gravel" and "concrete"), to significant types of connected parts like "stairs", "doors", "windows" and characteristic contiguous objects, e.g. "gas pump" (which actually occurs only in the pattern associated to the "gas station"), "tree", "pole" or "car" (whose multiple instances are usually located nearby parking lots or garages). The association between buildings and features mirrors the actual spatial arrangement of related entities in the FTIG environment.

In the first experiment (Figure 4), we fed the cognitive system with all the permutations of the walls constituting a single building (in the specific case "restaurant"), alternatively generating a consistent feature ("stairs") or an inconsistent one ("tree"). The knowledge component is triggered and combined with metric computations only when the consistent object is encoded and recognized as such by the hybrid cognitive system (using SCONE), whereas only metric computations activate when inconsistent objects are recognized as such. In this regard, we refer to the combined recognition mechanism as "contextual" prediction, whereas the metric-based similarity evaluation is referred to as "simple" prediction. This distinction, which applies to all the experiments presented in this section, is exposed by figures 4-7, where graphs on the left columns represent the average results across visual conditions for the simple prediction (where only *partial matching* based on walls dimensions is used), whereas the graphs on the right column depend on factoring in contextual reasoning validation (which translates to *spreading of activation* from the detection of consistent objects to related building patterns in the prediction mechanism).

In the second experiment (Figure 5), we augmented the complexity of the test by generating all the permutations to walls of two different buildings, the "mayor's mansion" and "service station", which are relatively similar in terms of the height and width of walls but obviously different, from a human standpoint[4], with respect to semantic connotations and telicity[5]. In this case, we assessed that the recognition of the "gas pump" clearly helps to disambiguate the context, especially in the less informative situations, where only one or two walls are detected. This remark generally holds for every experimental condition that we considered: the higher the number of walls successfully associated to the correct building, the smaller the discriminatory effect of the ontology (though it can still be crucial for the refinement of specific algorithms – e.g. path planning).

For the sake of testing increasing complexity, in the third experiment, wall permutations relative to three buildings were generated ("garage", "townhouse" and "crypt") and alternately coupled with two features ("opening" and "grass"), respectively consistent with two different buildings. As figure 6 indicates, while the process based on purely metric similarity was in average retrieving the "townhouse" as the most likely candidate, adding the ontology-driven cognitive mechanism allows to discard that result and boosts the recognition of the "garage" and the "crypt". "Grass" was also a pertinent feature of the "church" building, and this is reflected by the probability of activation of the corresponding pattern (labeled as "C" at the extreme left of the figure).

The final experiment concerned the "church", the most complex building of the test set, whose peculiar configuration is generally unique in the FTIG site. Although being morphologically distinctive in a given environment might be seen as an unconditional advantage for the prediction task, in practice the unusual spatial configuration of the walls, the singular presence of a bell tower as part of the building and the heterogeneous heights and widths of the constituent walls imply that the cognitive system needs to analyze an extensive information stream, in terms of geometric characteristics, conceptual and temporal structures. This complexity is clearly reflected by the results reported in the left columns of figure 7, where the probability value of the church pattern is slightly higher than the others, but overall extremely low in all four conditions. The right column shows, instead, that validation by knowledge boosts the value of the predicted patterns, even if - by using the shared surrounding feature

[4] Since the final objective of the cognitive system is to be deployed in a robot working with soldiers as a team member, sharing mental models with them is important.

[5]Telicity denotes the property of operational/social functionality assigned to artifacts.

"concrete" - the two patterns for "crypt" and "restaurant" are almost equally retrieved.

Because of the computational requirements of this knowledge-intensive simulation framework, we could not extend the experimentation beyond wall permutations of three buildings and three objects, although we aim at reporting these results in future work. Nevertheless, we think that the general trends of the predictions properly reflect the benefits of using ontology-based cognitive reasoning in conjunction with probabilistic computations, notwithstanding the intrinsic limits of assessing the cognitive system independently from the deployment in robots.

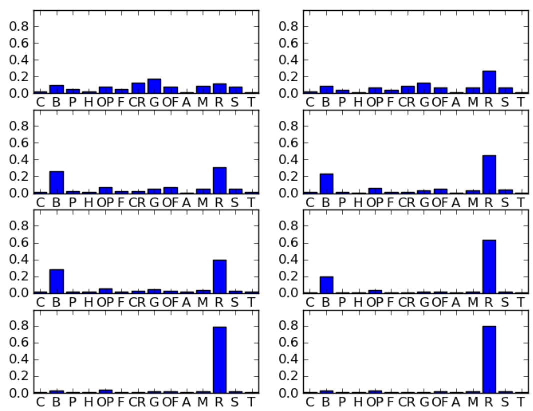

Figure 4

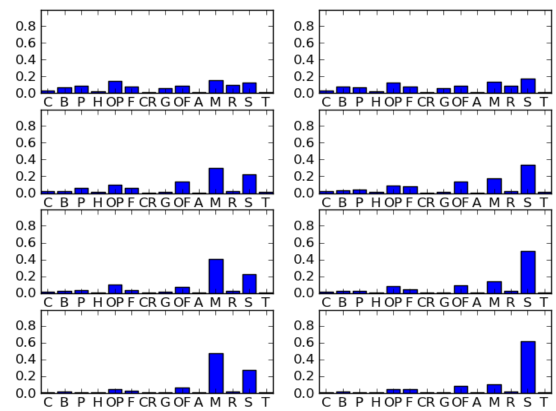

Figure 5

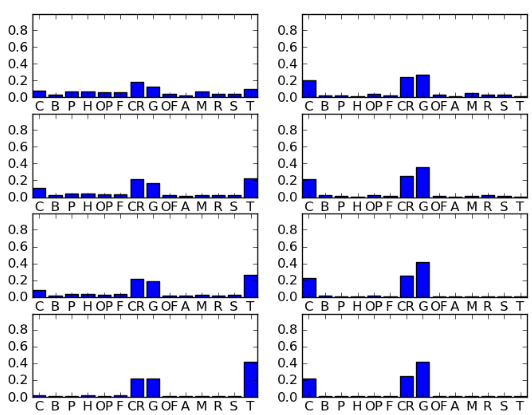

Figure 6

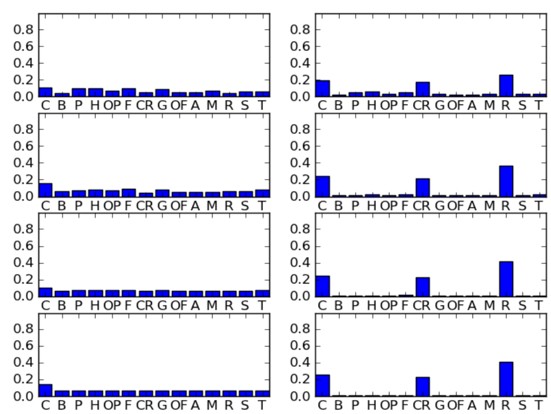

Figure 7

LEGENDA**:** Y-axis: probability associated to a building prediction; X-axis: labels for the14 buildings considered (C: Church; B: Bar; P: Police Station; H: Hotel; OP: Ops Storage; F: Fire Station; CR: Crypt; G: Garage; OF: Office Building; A: Aid Station; M: Mayor's House; R: Restaurant; S: Service Station; T: Townhouse.

Conclusion and Future work

In this paper we presented a hybrid cognitive system for high-level pattern recognition and contextual reasoning in a robotic framework. We showed how the integration between cognitive architectures and ontologies could leverage human-like capabilities in simulating building recognition task in a navigation scenario. Future work will be devoted to a broad validation of the system with respect to real-world test cases, where the hybrid system will be enhanced both in terms of learning capabilities and quantitative spatial reasoning.

Acknowledgements

The authors thank Martial Hebert, Arne Suppe and Unmesh Kurup for providing inspired ideas and insightful discussions. This work was conducted through collaborative participation in the Robotics Consortium sponsored by the U.S Army Research Laboratory under the Collaborative Technology Alliance Program, Cooperative Agreement W911NF-10-2-0016.

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