Virtual Humans: Evolving with Common Sense

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Abstract. While the quality and robustness of animation techniques for virtual human have improved greatly over the past couple of decades, techniques for improving their intelligence have not kept pace. Ideally, agents would be smart without being all-knowing and their future behaviors would be affected by their acquired knowledge just as with their real human counterparts. In this paper we present a method that uses commonsense knowledge to establish a baseline of concepts and relationships between objects. An agent then learns environment specific knowledge through its own perception and communication with other agents. Ultimately, agents' commonsense knowledge is then refined by their own experiences.

Keywords: Virtual Humans, Commonsense Knowledge, Explanation-Based Learning, Perception

1 Introduction

Virtual Humans are now being utilized in many applications such as games, movies, urban planning, and training and tutoring systems. With fast improving graphics hardware, they are likely to be pervasive in more and more domains. A critical aspect of virtual humans is their believability. In general, believability can be augmented in two means: visual quality and intelligent behaviors. For the past couple of decades, the visual quality of virtual characters has advanced dramatically. However, in terms of intelligence, progress has not been nearly so dramatic. In many applications, we still see largely hand-crafted and scripted behaviors which result in monotonous and unreasonable action patterns. While it is not clear when we might expect virtual characters with true human-level intelligence, certainly advancements are possible now. In this work, we focus on providing virtual humans with both general, scenario-independent knowledge and the ability to learn contextual knowledge. Agent behaviors then reflect their current understanding in terms of both commonsense knowledge and knowledge of their world.

Most real adult humans have a wide range of general, shared knowledge. Virtual humans, on the other hand, are either omniscient, greatly lacking in knowledge, or endowed with only scenario specific knowledge. When agents know everything their resulting behaviors can be unreasonable. If they have never been to or heard about a location, then they should not know to go there to retrieve an item. On the other hand, a limited, scenario specific knowledge base can prevent emergent behaviors and make authoring new scenarios too labor intensive. To mitigate this, we use Cyc [18], a well articulated commonsense knowledge base, to enrich our agents' knowledge. While Cyc is not considered complete in terms of all commonsense knowledge, its millions of concepts can take our virtual characters a step closer toward real humans. For example, in a first-person-shooter, Non-Player Characters (NPCs) could understand what objects are hard enough to be bullet proof and which ones are not and use that knowledge to find appropriate cover. Additionally, we are grounding the concepts and knowledge from Cyc in virtual worlds, but they remain scenario-independent so they can be applied in many different settings and environments without major modifications.

Nevertheless, a large amount of commonsense knowledge is not sufficient. Virtual humans also need to obtain information specific to the virtual world they are inhabiting. They need to learn what resources are available and where they are. While the ability to learn has been successfully deployed in robots, interactive characters, and software agents, its implementation in virtual humans needs further exploration. This is especially critical for NPCs in games. With increasingly complex game environments and highly adaptive players, not only do traditional AI techniques face creation and maintenance problems [17], but NPCs that cannot learn end up perverting the gaming experience over time [26]. In this work we focus on learning about the virtual world through both direct observation and explanation from other virtual humans. We feel these are the two most common ways that people develop knowledge of the world they live in. In particular, we deploy a perception system and exploit Explanation-Based Learning (EBL) to enable agents to expand their prior knowledge and obtain new information.

In summary, the goal of this work is to try to improve virtual humans through more intelligent, emergent behaviors. To accomplish this, we provide our virtual humans with a vast amount of commonsense knowledge and bestow them with the ability to learn and evolve. Specifically, we explore the use of Cyc, a well designed commonsense knowledge base, and simulate learning both by observation and explanation. To better demonstrate the effectiveness of our approach, in a later section we will provide several examples in which our agents gain more believable, contextual behaviors. A diagram of our current system illustrates the information flow is shown in Figure 1.

2 Related Work

For the past decade, researchers have invested effort in creating life-like behaviors for virtual characters, including simulating the decision-making process and developing action selection mechanisms. Some researchers have favored complex

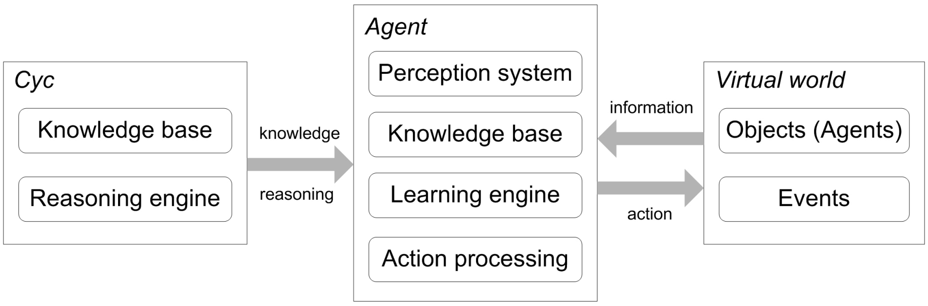

Fig. 1. System Diagram

computational methods such as Bayesian networks [14], decision networks [35] and fuzzy logic [15]. Others have addressed this problem from a cognitive perspective. For example, Funge et al [11] developed a cognitive modeling language for modeling behaviors of intelligent characters. Paris et al [28] incorporated a cognitive model into a crowd simulation. Goertzel et al [12] proposed a cognitive synergy approach for both animated and robotic agents. In addition, many works have demonstrated the use of various social psychology factors in order to generate reasonable, heterogeneous agent behaviors such as in [29, 20] and also a group of work has been inspired by the BDI architecture [31]. While significant results have been made, most of above mentioned work provides their agents with limited domain-specific knowledge and assumes the agent knowledge base is complete when the simulation begins, which not only prohibits the agents from learning and evolving, but also limits their emergent behaviors and makes new environment adaption difficult.

In comparison, several research groups have worked toward endowing virtual characters with an ability to learn. Cohen and his colleagues [6] have built a baby agent which is capable of learning conceptual knowledge using sensorimotor interactions with a simulated environment. In [3], Blumberg et al integrate learning activity into a virtual dog and allow users to train the dog by interacting with it. For virtual humans in 3D environment, Conde et al [7] adopt a reinforcement learning approach to assist agents with path-finding tasks. Orkin et al developed a restaurant game [27] in which collected behaviors and dialogs can be used by NPCs to enhance the gaming experience. However, the learning phenomenon in these works are between an agent and the user or environment, not among the characters themselves. These previous approaches can either demand a lot of real human effort and limit agent interactions with other agents. To summarize, we believe invoking learning activity between virtual agents in addition to the environment would add more reasonableness and believability to them and also allow them to evolve more autonomously.

Other research, such as Cyc [18], ConceptNet [33] and WordNet [10], has focused on collecting broader or commonsense knowledge with applications in, for example, clinical question answering [19], conversational agents and storytelling

[34, 5], interface agents [21], text-to-scene generation [8], and culture difference studies [2]. While these applications have made interesting and promising showing in the use of commonsense knowledge, most are related to software agents development and natural language processing. In autonomous agent design, He et al [13] proposed a multi-agent architecture using commonsense knowledge. Rafique [30] wrote his Ph.D. thesis on commonsense reasoning in autonomous intelligent agents. However, neither of their works address virtual characters in rich 3D environments for simulations or games. Believing there is potential in using commonsense knowledge in animation and games, in this paper we present work that combines commonsense knowledge with learning methods to create agents that demonstrate more contextual and consistent behaviors.

3 Commonsense Knowledge

Commonsense knowledge is knowledge about everyday things that ordinary people possess but computers do not. Its importance has been recognized and established by many researchers such as McCarthy [22], Lenat [18] and Minsky [24]. It has also been labeled a bottleneck in making computers truly intelligent [18, 24]. While software with commonsense knowledge is a promising and interesting topic, its development has met several hurdles and thus its usage is not prevalent. We believe there are several reasons for causing that. First of all, to represent knowledge, different commonsense knowledge bases have adopted different approaches. To be specific, Cyc uses logic, a formally unambiguous form for representing concepts; ConceptNet exploits semi-structure natural language, treating each concept as a node in a hypergraph; WordNet organizes all the words (e.g. nouns, verbs, adjectives, and adverbs) in an ontological structure and mainly uses hyperonymy and hyponymy relations to connect them. These different approaches all have certain advantages and disadvantages and thus make each one of them more suitable for certain applications over the others. Secondly, the definition of "common sense" is intrinsically vague which can cause concepts to vary widely between knowledge bases and for some uses a piece of knowledge may seem too general but for others too specific. A third reason the use of commonsense knowledge bases has not become more prevalent is related to the potentially enormous amount of knowledge they could contain. And none of the knowledge bases is able to claim that it contains all pieces of commonsense knowledge at this point. As a result, for certain scenarios, the use of commonsense knowledge seems inapplicable. For example, in those applications which users have high expectations (e.g. expert systems), if the agent does not provide a correct response on the first try, a user's trust is lost.

In spite of these issues, researchers have been able to take advantage of commonsense knowledge bases. As noted in [21], for interface agents, where the main use of commonsense knowledge is to provide suggestions and alternative options, promising results have been achieved. In addition, for natural language related applications, since vagueness and ambiguity is inevitable and sometime even desirable, the use of commonsense knowledge is becoming popular (We have listed a few in the previous section). Also, some researchers have started to use combination of different commonsense knowledge bases in developing their project [26]. In the work presented in this paper, we extend and ground the usage of commonsense knowledge in applications related to animation and game research. While the use of commonsense knowledge is not prominent in this community, we believe our virtual humans can benefit from it for a couple of reasons. First, users should expect virtual humans to obtain as much commonsense as real humans do and reason and behave upon it. This means limited and constrained knowledge is not going to support highly believable, reasonable behaviors. Secondly, scripted knowledge is usually scenario-dependent which limits an agent's emergent behaviors to a great extent and also makes expansion of new scenarios labor intensive (i.e. new knowledge needs to be incorporated into the system to fit in new scenarios). Commonsense knowledge can help to overcome these drawbacks. Even though none of the knowledge bases is considered exhaustive right now, they can greatly extend an agent's knowledge from dozens or hundreds of concepts in current applications to millions of highly scenario independent concepts.

Among several commonsense knowledge bases, we have chosen Cyc for further exploration. Particularly, we are using OpenCyc, an open source version of Cyc with full knowledge items. We are using Cyc for the following reasons. First of all, Cyc is the *world's largest and most complete general knowledge base and commonsense reasoning engine* [1]. Cyc has been successfully deployed in many applications and numerous users have exploited it for their own projects (a list of current and potential applications can be found in [1]). Secondly, Cyc uses its own logic-based language CycL for representing knowledge. There are several advantages in using a logic representation. One is that logic is unambiguous and can facilitate reasoning. Another is that it still preserves expressiveness which makes it suitable for natural language related applications. Thirdly, the built-in search engine in Cyc is well optimized making the searching process very fast and efficient. For an extensive tutorial of Cyc, CycL and more, we refer readers to their official website [1]. Finally, we would like to note that even though we are using Cyc in this work, the learning strategy presented in the next section is not dependent on a particular commonsense knowledge base. In the future we may explore other knowledge bases and even the combinations of knowledge bases.

4 Learning Activity

The learning activity of real humans is very sophisticated and its exact nature is still being uncovered. However, it is generally accepted that it contains several approaches, such as explanation-based learning, instance-based learning, analogical learning, and reinforcement learning. Given the complexity of this problem, we do not intend to capture all aspects of human learning. We will concentrate on learning by explanation and observation. Learning by explanation and observation is one of the main approaches humans use to obtain knowledge. For example, there are students learning from teachers, trainees acquiring skills and duties from a supervisor, and visitors adopting cultural differences from their hosts. In following sections, we will outline two forms of learning: agent-from-agent and agent-from-environment.

4.1 Agents Learning from Other Agents

For learning between agents, we use Explanation-Based Learning (EBL). EBL is an analytical learning method which acquires new knowledge and concepts based on prior knowledge, explanation, observation and information expansion of training examples [25, 9]. We have adopted EBL because other learning methods seem less applicable in this context. Inductive learning methods, such as decision tree learning and neural networks, usually require abundant examples which our application does not have. Instance-based learning which requires similar examples to make a comparison faces the same problem. Statistical methods, such as Bayesian networks, are also not ideal because of a need for crafted probabilities. In addition, we do not attain any direct and/or indirect reward and penalty feedback as a training source which is needed to carry out reinforcement learning. With these considerations in mind, we believe EBL is the most plausible and applicable method for simulating learning by explanation and observation.

Generally speaking, EBL contains four components: a *Goal Concept*, a target concept with a set of relevant features; a *Training Example*, a typical positive example of the goal concept; *Domain Theory*, prior knowledge used to analyze and explain why training example satisfies the goal concept; a *Learned Rule*, a generalized rule learned from prove of the positive example using domain theory. An example of EBL is provided below:

- Goal Concept: $MailToProfA(x)$
- Training Example: A positive example, $MailToProfA(Obj1)$
  $Inside(Obj1, Office\_0)$
  $Inside(Obj1, Obj2)$
  $Type(Obj1, Mail)$
  $Type(Obj2, Box)$
  $Color(Obj1, Red)$
  $Color(Obj2, Green)$
- Domain Theory:
  $MailToProfA(x) \leftarrow Location(x, Office\_0) \wedge Inside(x, y) \wedge Type(x, Mail) \wedge Type(y, Box) \wedge Color(y, Green)$
  $Location(x, Office\_0) \leftarrow Inside(x, Office\_0)$
- Learned Rule:
  $MailToProfA(x) \leftarrow Inside(x, Office\_0) \wedge Inside(x, y) \wedge Type(x, Mail) \wedge Type(y, Box) \wedge Color(y, Green)$

One of the critical features of EBL is the assigning prior knowledge. We use a commonsense knowledge base to aid in this process. In this learning scenario, we treat knowledge concepts in Cyc as the base or prior knowledge for our agents.

For instance, in the above EBL example, three categories of prior knowledge have been used. They are colors (e.g. *Red*, *Green*, *Blue*), spatial relationships (e.g. *Inside*, *Outside*, *Above*), and object types (e.g. *Mail*, *Box*) and instances (e.g. $Office\_0$). These concepts, except the object instances which are generated from their parent object types, are all provided by Cyc or in other words they all have an entry in the Cyc knowledge base. As you might imagine, the large number of concepts stored in Cyc combined with EBL provides the potential for virtual humans to acquire an enormous amount of new knowledge and concepts.

Agent-from-agent learning requires certain coordination between the agents. So, for each *Learner* and *Instructor*, we have designated actions *Observe* and *Explain* respectively. The positive example and domain theory are then put into a database with an additional boolean field initially set to 0 to indicate the learning status. Once the learner begins to *Observe* and the instructor starts to *Explain*. An underlying iterative algorithm will start to prove the positive example using domain theory. If this step concludes successfully, the learning status will change from 0 to 1 to imply that learning process is complete. Next, the proven positive example will be generalized into a rule and this rule, the newly learned knowledge, will be put into the learner's knowledge base. The learner can then perform the corresponding behaviors associated with this piece of knowledge. For example, the final learned rule in above example states "*Mail* x is for *ProfA* if x is inside *Office_0* and inside y which has type *Box* and color *Green*". With this newly learned knowledge, the learner can execute behaviors such as "Deliver *ProfA*'s mail to his box" and "Retrieve *ProfA*'s mail from his box".

4.2 Agents Learning from the Environment

In addition to learning from other people, humans can also learn through direct observation of their environment. For example, every time you walk into a store you refine your knowledge of the items found there. Then when you need to purchase a certain item you have a better idea of which store to look in and where in the store to find it. This learning mechanism is pervasive and powerful. However, knowledge formation in this process requires not only a functional perception system but also other elements such as memory and desire. According to psychologists, there are several different types of memory. One type, *Declarative Memory*, can be further decomposed into *Long-term Memory* and *Working Memory*. Long-term memory stores long-lasting facts while working memory tracks information related to immediate tasks (for more information on memory classifications we refer readers to [32]).

In this work, we are currently assuming that our agents have the desire to update their knowledge about the environment and they have perfect *Long-term Memory*, meaning they will not suffer memory loss. As far as perception, many factors can have an impact. For instance, larger items with dazzling color and peculiar shape tend to draw attention [16]. As the focus of our current work is improving agent intelligence and not implementing a comprehensive perception system, we focus on just the following factors that can influence agent perception:

Size, a large object is easier to see; *Quantity*, while many items could appear in a location human *Working Memory* can only store 5 to 9 objects at a time [23]; *Occurrence Rate*, the number of times an agent has seen an object in a particular type of location; *Object Location*, an agent needs to know object locations in order to retrieve them later. When updating its knowledge base with objects, an agent also updates the object locations.

Details of our implementation of learning from the environment are as follows. First we search the Cyc knowledge base for a list of objects associated with a certain place. For example, Cyc searches for "kitchen" yield "kitchen tool" and an association with "microwave oven", "pan", "blender", and "cutting board" (among others). Next we add this object list to the agent's knowledge base with an occurrence rate of 1. These objects become a part of the agent's initial definition of a certain place (e.g. kitchen). As agents operate in an environment, they encounter places for which they have definitions in their knowledge bases. They refine these definitions in accordance with their experiences. For example, if a place contains contains n objects, agents do the following: if $n \leq 5$, update their knowledge bases with all n objects; if $n > 5$, generate a random number m between 5 and n and update their knowledge using the m objects with the biggest size. The updating procedure is: if the object already exists in an agent's definition of such a room, increase the occurrence rate with 1; otherwise under the definition of such a room, create an entry for the object and label its occurrence rate with 1; update the location of each object that the agent is using to refine its knowledge base.

We believe mechanisms for enabling agents to learn about their environment leads to more reasonable behaviors than programming omniscient agents. The same observation is shared by many researchers. For example, Burke et al [4] call this *Sensory Honesty* and provides additional justification for its necessity.

5 Examples

In this section we will provide a few more detailed examples to better illustrate our agents use of commonsense knowledge and their learning techniques. Our first example involves agents learning from each other. In this example, we have two agents, a *Learner* and a *Instructor*. The learner is tasked with learning several administrative related concepts from the instructor. The learner then applies behaviors according to his newly acquired knowledge. For simplicity, here we only list the learned rules in EBL form:

– $ReadyForPost(x) \leftarrow Inside(x, Hallway\_1) \wedge Above(x, y) \wedge Type(y, Table) \wedge Color(y, Yellow)$
– $LeftInLibrary(x) \leftarrow Inside(x, Library) \wedge \neg Type(x, WhiteBoard) \wedge \neg Type(x, Desk) \wedge \neg Type(x, Chair) \wedge \neg Type(x, Shelf) \wedge \neg Type(x, Light)$
– $NeedWatering(x) \leftarrow Type(x, Plant) \wedge Color(x, Yellow)$

The first rule states if an object is inside hallway_1 and above a yellow table then is ready for post. With this knowledge, the agent will know where objects ready to be posted are stored. He can then retrieve these objects and post them on the bulletin board. The other learned rules result in similar corresponding behaviors. Figure 2 shows screen shots of the agent learning and preforming activities.

Fig. 2. Learner acquires several concepts (i.e. *ReadyForPost*, *LeftInLibrary* and *NeedWatering*) and later performs corresponding behaviors (e.g. *Post Flyers*, *Check Library* and *Water Plant*).

In our second example, agents learn and refine their knowledge through observation of the environment. Cyc provides our agents with an initial definition of a place. For example, a kitchen contains a microwave oven, a pan, a blender and more. Given this definition, agent can search for an item in the kitchen and refine his knowledge by observing the space. Also, an agent can learn about additional locations by traversing the environment or by communicating with other agents. Figure 3(a)-(c) illustrates such a scenario: first an agent travels to a kitchen, refines his knowledge and gets a banana. Then during his way back, another agent informs him of a closer kitchen. Later, the agent reflects this newly learned knowledge by searching the closer kitchen for kitchen related items. In another case, as agents encounter new places in their environment, they attempt to use their commonsense knowledge to define or categorize the spaces. Figure 3(d)-(f) shows an agent discovering a room with a fridge, a laboratory desk, a printer, and a copy-machine. The agent considers how often he has seen these objects other already defined rooms. For example, his occurrence rates for these objects in a laboratory is 3, 20, 15, and 12. For kitchens they are 25, 1, 5, and 4. Summing the occurrence rates for the objects, we see that laboratory scores 50 and kitchen scores 35, resulting in the room being classified as a laboratory. The agent's future behavior will now reflect that he considers this room a laboratory.

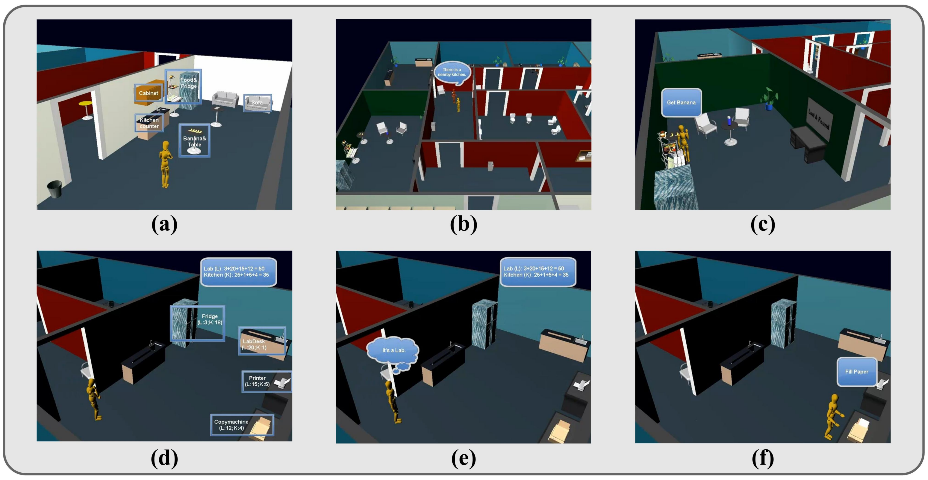

Fig. 3. (a) An agent travels to a kitchen and refines his knowledge. (b) Another agent informs him of a closer kitchen. (c) Later the agent searches the closer kitchen first when he wants a kitchen related item. (d) An agent uses his knowledge to categorize a new place. (e) Given objects occurrence rates, he classifies the space as a laboratory. (f) Later when the agent is asked to put paper in lab copy-machines, he includes this newly defined location.

6 Discussion and Future Work

Our goal is to improve the behavior of virtual humans, make them closer to real human behaviors, and facilitate the use of virtual humans in games and other simulations. In particular, we have presented techniques for supplying agents with a foundation of commonsense knowledge and for accumulating and contextualizing their knowledge through interactions with the environment and other agents. Agents should be smart without being all-knowing and their future behaviors should be affected by their acquired knowledge just as with their real human counterparts.

Additional work is required to obtain even more realistic behaviors. In particular, more detailed perception and memory systems need to be modeled. What we perceive in a scene is affected by a number of factors including the properties and motion of the objects, but also our own state of mind. Our current goals and focus also influence both our creation of memories and our recall ability. Given the imperfect nature of humans, how much accuracy and specificity is needed in these sub-systems to generate agents behaviors that are plausible and acceptable to real human observers? Human observers do tend to notice when agent behaviors demonstrate a lack of knowledge they would deem commonsense. The various knowledge bases have different characteristics. Instead of solely using Cyc, we would like to explore more of the semantic network and see if additional resources could help strengthen the current system. The work presented here focused on aspects of the environment and the objects in it. It might also be interesting to explore the representations of actions and their consequences.

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