A logical framework for describing machine knowledge

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Abstract

Knowledge acquisition and autonomy has been a bottleneck in machine intelligence research. This paper proposes a logical framework for describing machine knowledge. The so-called "machine knowledge" refers to the knowledge acquired by robot systems in the following way. A robot uses its sensors to sense the external environment, and the sensors transfer the external states (environment) to the robot's memory in the form of sensing data, then the robot converts the data into knowledge through the system mechanisms, and the knowledge is stored in the robot's knowledge base, forming its own internal state(for environment awareness). Robots can autonomously use their knowledge when planning and making decision without any external intervention. The aim of our work is modelling the above process including formal representations for sensors, sensing data and knowledge, a mechanism converting sensing data to knowledge and automatically updating the internal state of the robot. The main contribution of this paper is to present a new approach for researching machine intelligence, which develops along the direction of “machine code–machine data–machine knowledge–machine intelligence”. The proposed logical approach does not involve the modal logic, and its semantics is based on the sensing data rather than possible world models.

Keywords: artificial intelligence; machine knowledge; sensing data; autonomous robot; logical framework

1 Introduction

To make machine have intelligence researchers try to put human intelligence on machine (make machine have the function like human intelligence). However, it is not easy to do so. Some machine readable formal languages and semantics are needed for describing knowledge and mental states. Hintikka[1] developed the first modal logic of knowledge and applied Kripke’s ideas to his new logic. He considered an accessible relation on possible worlds, and defined knowledge by accessibility relations. McCarthy and Hayes[2] suggested using Hintikka’s logic for representing an agent’s knowledge. During the past decades, modal logics and possible world semantics have become one of the most important logical tools for representing agents’ knowledge and mental attitudes such as belief, desire, intention, emotion, consciousness etc. And a variety of improved methods continue to appear. For example, some recent research publications are as follows.

Lakemeyer and Levesque[3] proposed a new logic called ES to discuss some properties of knowledge. The proposed language includes a modal operator *Know* for knowledge. In this way the situations will be modeled where a robot has false beliefs about its world or how its world changes. They isolated a fragment of the situation calculus with knowledge (presented using a modal syntax) and showed it to have a relatively simple model theoretic semantics based on possible worlds. The interpretation of knowledge in ES is a special case of possible world semantics. French etc[4] discussed the issue on comparing knowledge representation formalisms. They presented a number of succinctness results related to three well-known extensions of multimodal logic (ML) which have a popular epistemic and knowledge representation interpretation. They tried to answer the question of whether a particular formalism can express some property on some class of models or not. Yan Zhang and Yi Zhou[5] studied a formal notion of knowledge forgetting in S5 modal logic. They proposed four postulates that precisely characterize both semantic and logical properties of knowledge forgetting. And they also investigated possible applications of knowledge forgetting in various epistemic reasoning scenarios. Lijun Wua etc[6] extended the logic of knowledge, belief and certainty from one agent to multi-agent systems, and combined the extension of the logic and actions that have concurrent and dynamic properties. Based on it, they presented a concurrent dynamic logic of knowledge, belief and certainty for MAS. The modality in the proposed logic has concurrent properties. Saint-Cyr and Lang[7] studied the issue on reasoning about change in knowledge representations. They proposed a logical framework for reasoning with observations at different time points. A very general and structured class of extrapolation operators and belief extrapolation are defined. This work shows that belief extrapolation can be seen as a particular belief revision process, where the beliefs about the persistence of fluents are revised by timestamped observations. Britz etc[8] discussed preferential reasoning for modal logics and their semantics. Before that there was no generally accepted semantics, with corresponding syntactic characterization, for preferential consequence in modal logics. This work fill this gap by providing a natural and intuitive semantics for preferential and rational modal consequence. The proposed modal se-

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mantics forms the foundation of preferential consequence for a whole class of modal-based formalisms. Moreno and Miguel[9] introduced application of machine consciousness models in autonomous situated agents and described the most relevant current approaches to the implementation of scientific models of consciousness. Depending on the conscious or unconscious nature of the processes, knowledge can be declarative or procedural, localized or distributed, serial or parallel. Knowledge representation is implicit in unconscious processes and explicit in conscious processes. the cognitive processes are structured in these two levels with different mechanisms. Reggia[10] introduced the rise of machine consciousness ---- Studying consciousness with computational models. He explained some of the concepts and terminology used by investigators working on machine consciousness, and summarized key neurobiological correlates of human consciousness that are particularly relevant to past computational studies.

Besides knowledge and metal attitudes, intelligence also contains other features. Luger[11] believe that intelligent systems should satisfy the four criteria that are situated, autonomous, flexible, and social. Autonomy has always been a challenge in robotics research. A autonomous robot is one that able to act adaptively to the unknown or dynamic environments[12]. To do this an internal model of robot needs to be designed not only with the ability of information processing in response to external stimuli, but also with the ability of self-control. Adaptive behaviors of robots are driven by the internal model depend on the observation of both external environment and internal state. Kuremoto etc[13] proposed an improved internal model of autonomous robots to evoke robots actions using a psychological theory of Russell. The results showed that robots with the improved model can move dynamically and successfully reach at multiple goal areas avoiding local traps and obstacles in the complicated environment. In dealing with dynamical complex environment and acquiring collaborative behaviors of autonomous robots, ‘‘mental’’ states of robots play important roles during the decision process of actions.

Although there have been a lot of researches on developing machine intelligence, most existing AI systems and robots are not autonomous. The greatest challenge to achieve robot’s autonomy is how to describe the internal states and internal knowledge of robots. It is needed to distinguish three objects, the robot, the designer and the user in designing autonomous robots. Reiter[14] indicated: the moment one chooses to take knowledge seriously in axiomatizing a domain, it becomes very important to understand the role of the designer – the person who writes the axioms – and her relationship to the agent whose state of knowledge she is axiomatizing. The knowledge built by the designer for robots belongs to “built-in knowledge”. And the knowledge built by the user (or the operator) for robots belongs to “external knowledge”. Robots with “built-in knowledge” and“external knowledge” lack autonomy. An autonomous robot should be able to axiomatize its knowledge and environment by itself.

Modal logics and possible worlds semantics have great limitations for describing the autonomy of robot. Morgenstern and McIlraithb[15] argued that McCarthy had maintained an ambivalence toward any modal logic. His ultimate goal had been to formalize intelligent reasoning within first-order logic, or something as close to first-order logic as possible. Herzig[16] overviewed the most prominent logics of knowledge and action that were studied in the multiagent systems literature. There are weaknesses in the design of these logics and arguments on their suitability to represent knowledge and reason about it. Accessibility relations in possible world semantics is an important factor that can not well represent autonomous robots’ knowledge. Robots are incapable of designing accessibility relations in an unknown environment. Accessibility relations must be designed by the system designers or external operators.

It is well known that data, information, knowledge and intelligence are intrinsically linked[17,18]. Inspired by this thought, we propose a new approach for describing robot’s knowledge, which focus on the characteristics of machine. In other words, we research machine intelligence along the evolutionary direction of “machine code–machine data–machine knowledge–machine intelligence”. we proposes a logical framework for describing machine knowledge. The so-called "machine knowledge" refers to the knowledge that a robot uses its sensors to sense the external environment, and the sensors transfer the external states (environment) to the robot's memory in the form of sensing data, then the robot converts the data to knowledge through the system mechanisms, and the knowledge is stored in the robot’s knowledge base, forming its own internal state(for environment awareness). Our logical approach does not involve the modal logic, and the proposed semantics is based on the sensors rather than possible world models. The aim of our work is modeling the above process including a formal representation for sensors, sensing data and knowledge, a mechanism converting sensing data to knowledge and automatically updating the internal state of the robot.

The rest of the paper is organized as follows. In the next section we introduce the syntax and semantics of $\mathrm{L_{MK}}$ and discuss sensors, sensing actions and sensing data. In Section 3, we design a mechanism for converting sensing data into knowledge and automatically updating the internal state of the robot. Section 4 provides the an application example of the logical framework to show the autonomous performance of robots in $\mathrm{L_{MK}}$. Finally we end the paper with a conclusion.

2 A logical framework for machine knowledge

In this section we build a logical framework $\mathrm{L_{MK}}$ for describing machine knowledge. $\mathrm{L_{MK}}$ is an expansion of the traditional situation calculus action theory by adding two kinds of sensors and defining a novel semantics based on sensing data. Most concepts and symbols concerned action theories and situation calculus in this paper can see[19,20].

2.1 THE SYNTAX OF $\mathbf{L_{MK}}$

The syntax of $\mathrm{L_{MK}}$ is constructed as follows:

1. The alphabet in $\mathrm{L_{MK}}$:
   - The alphabet of the standard first order logic;
   - Countable infinite many individual variable symbols for action: $a_1, a_2, \cdots$;

- Countable infinite many individual variable symbols for situation: $s_1, s_2, \cdots$;
- Countable infinite many individual variable symbols for object: any usable symbol.
- Finite specific functional constant symbols: $\boldsymbol{f}, \boldsymbol{g}, \boldsymbol{h}, \cdots$, these specific symbols correspond to the functional sensors fixed on robots.
- Finite specific predicate constant symbols: $\boldsymbol{P}, \boldsymbol{Q}, \boldsymbol{R}, \cdots$, these specific symbols correspond to the relational sensors fixed on robots.

2. The formation rules of terms and well formula are the same as in the standard first order logic and the traditional situation calculus.
3. The inference rules in L_{MK} are the same as in the standard first order logic and the traditional situation calculus.

2.2 SENSORS, SENSING ACTIONS AND SENSING DATA IN L_{MK}

Suppose that robots are equipped with multiple sensors. The sensors here are mechanical settings fixed on robots. Each sensor has a specific function. For example, they can independently identify a desk, a book, or the position relationship between two objects, and so on. There are two sorts of sensors in our systems:

- Relational sensors, denoted by $\overline{BOOK}(\mathrm{x})$, $\overline{DESK}(\mathrm{x})$, $\cdots$, their functions are to check whether certain objects have a particular relationship. These sensors have tow output values "YES" and "NO". The value is "YES", if the relation holds; the value is "NO", otherwise. For example, the sensor $\overline{BOOK}(\mathrm{x})$ is used to check "whether x is a book"; the sensor $\overline{DESK}(\mathrm{x})$ is used to check "whether x is an eraser"; the sensor $\overline{ON}(\mathrm{x,y})$ is used to check "whether *x* is on *y*".
- Functional sensors, denoted by $\overline{dist}(x, y)$, $\overline{temp}(x)$, $\cdots$, their functions are to determine the value of some attribute of objects. The output values of these sensors vary in some range like a mathematical function. For example, the sensor $\overline{dist}(x, y)$ is used to determine "the distance between x and y ", the value of $\overline{dist}(x, y)$ varies in [0, +∞); the sensor $\overline{temp}(x)$ is used to determine "the temperature of *x*", its value varies in (-270, +∞).

Sensing actions are those robots perform using their sensors to get external environment information. For example, When a robot wants to check whether the object a is a book, the robot needs to perform a sensing action: starts the sensor $\overline{BOOK}(\mathrm{x})$ and use $\overline{BOOK}(\mathrm{x})$ to work on *a*. If a is a book, then the output value of $\overline{BOOK}(\mathrm{a})$ is "YES"; if a is not a book, then the output value of $\overline{BOOK}(\mathrm{a})$ is "NO". In the same way, when a robot wants to determine whether two objects b and c have the relation " b is on *c*", the robot needs to perform a sensing action: start the sensor $\overline{ON}(\mathrm{x,y})$ and use $\overline{ON}(\mathrm{x,y})$ to work on b and *c*. The output value of $\overline{ON}(\mathrm{b,c})$ will be "YES", if b is on *c*; the output value will be "NO", if b is not on *c*.

Sensing data come from robots' sensors. When a robot performs a sensing action, the corresponding sensor will return a sensing result. The system acquires sensing data from the (name of) sensor and its return value (YES/NO). Generally, there are two types of sensing data, relational sensing data and functional sensing data.

- the structure of relational sensing data: < name of sensor, object-1,object-2, ⋯, object-n, YES/NO>. For example, if the robot performs a sensing action: starts the sensor $\overline{BOOK}(x)$ and uses $\overline{BOOK}(x)$ to work on *a*, and the output value of $\overline{BOOK}(\mathrm{a})$ is "NO", then the system will acquire sensing data < BOOK, a, NO >; if the robot performs another sensing action: start the sensor $\overline{ON}(\mathrm{x,y})$ and use $\overline{ON}(\mathrm{x,y})$ to work on b and *c*, and the output value of $\overline{ON}(\mathrm{b,c})$ is "YES", then the system will acquire sensing data < ON, b, c, YES>. See figure 1.
- the structure of functional sensing data: < name of sensor, object-1,object-2, ⋯, object-n, value of attribute >. For example, if the robot performs a sensing action: start the sensor $\overline{dist}(\mathrm{x,y})$ and use $\overline{dist}(\mathrm{x,y})$ to work on b and *c*, and the output value of $\overline{dist}(\mathrm{b,c})$ is 6, then the system will acquire sensing data < dist, b, c, 6>.

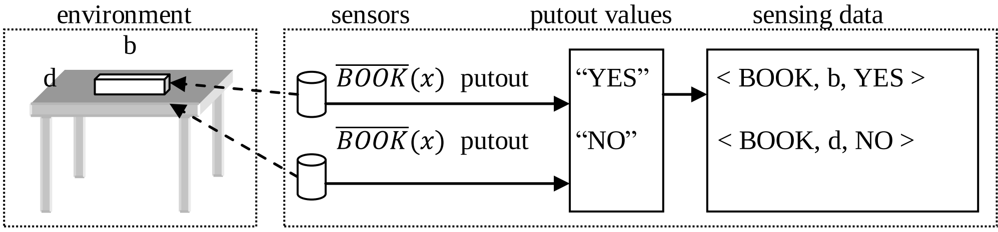

FIGURE 1 the sensing data generated by $\overline{BOOK}(x)$

2.3 THE SEMANTICS OF L_{MK}

In this section we define a semantics based on sensing data for L_{MK}. The semantic interpretations of the formulas in L_{MK} are defined as follows:

a) Let $\mathbf{P}(x_1, x_2, \cdots, x_n)$ be a specific atomic predicate formula in L_{MK}, $\bar{P}(x_1, x_2, \cdots, x_n)$ be its corresponding sensor, and $a_1, a_2, \cdots, a_n$ be individual objects in the robot's environment, then

$\mathbf{P}(a_1, a_2, \cdots, a_n)$ is true, if the robot receives sensing data < P, a_1, a_2, ⋯ , a_n, YES >;

$\mathbf{P}(a_1, a_2, \cdots, a_n)$ is false, if the robot receives sensing data < P, a_1, a_2, ⋯ , a_n, NO >;

b) $\neg\mathbf{P}(a_1, a_2, \cdots, a_n)$ is true iff $\boldsymbol{P}(a_1, a_2, \cdots, a_n)$ is false;

c) $\mathbf{P}(a_1, a_2, \cdots, a_n) \wedge \mathbf{Q}(a_1, a_2, \cdots, a_n)$ is true iff $\boldsymbol{P}(a_1, a_2, \cdots, a_n)$ and $\boldsymbol{Q}(a_1, a_2, \cdots, a_n)$ both are true;

d) $\mathbf{P}(a_1, a_2, \cdots, a_n) \vee \mathbf{Q}(a_1, a_2, \cdots, a_n)$ is true iff at least one of the two is true;

e) $\mathbf{P}(a_1, a_2, \cdots, a_n) \rightarrow \mathbf{Q}(a_1, a_2, \cdots, a_n)$ is false iff $\mathbf{P}(a_1, a_2, \cdots, a_n)$ is true and $\mathbf{Q}(a_1, a_2, \cdots, a_n)$ is false;

f) $\exists x\mathbf{P}(x)$ is true iff the robot receives sensing data < P, a, YES > for some object *a* in the robot's environment;

g) $\forall x\mathbf{P}(x)$ is true iff the robot receives sensing data < P, a, YES > for all object *a* in the robot's environment;

Figure 2 is an example of semantic interpretations based on sensing data.

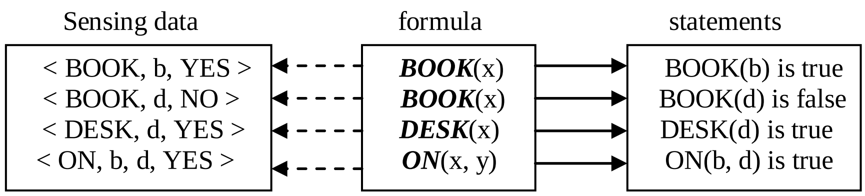

FIGURE 2 Semantic interpretations based on sensing data

The semantic interpretations of the specific functions in L_{MK} are defined as follows:

Let $\boldsymbol{f}(x_1, x_2, \cdots, x_n)$ be a specific function in L_{MK}, $\bar{f}(x_1, x_2, \cdots, x_n)$ be its corresponding sensor, and a_1, a_2, ⋯ , a_n are individual objects in the robot's environment, then $\boldsymbol{f}(a_1, a_2, \cdots, a_n) = v$, if the robot receives sensing data < f, a_1, a_2, ⋯ , a_n, v >.

This kind of semantic interpretation is a situated interpretation (by contrast, the classical first-order semantic interpretation is a model interpretation). Only the relevant objects in the robot's environment are considered.

3 Machine knowledge

3.1 ROBOT'S INTERNAL KNOWLEDGE

This section discusses the formation of internal knowledge for robots. To this end, a internal knowledge base IKB is built and a mechanism for converting data to knowledge is designed.

Internal knowledge base IKB. When a robot performs a sensing action (starts its sensors to sense external environment), the sensors will return their sensing results to the system in the form of data. Then the system converts sensing data to knowledge. For example, when a robot performs a sensing action: starts the sensor $\overline{BOOK}(x)$ and uses $\overline{BOOK}(x)$ to work on *a*, and the output value of $\overline{BOOK}$(a) is "YES", then the system acquires sensing data < BOOK, a, YES >; meanwhile, the system converts the sensing data < BOOK, a, YES > to knowledge " a is a book", where "a is a book" can be denoted by a predicate formula BOOK(a), or other forms. Knowledge acquired from sensing data by sensors will be stored in IKB. Knowledge in IKB is called internal knowledge of robot.

IKB updating. IKB of robot will be updated while the robot performs sensing actions. The rules of IKB updating are as follows.

1) If the new sensing data and the original sensing data are the same, then the original sensing data and knowledge are retained.
2) If the new sensing data and the original sensing data are not the same, then replace the original data with new data; meanwhile replace the original knowledge with new knowledge in IKB.

3.2 ROBOT'S MENTAL STATES

It is needed to representing robot's mental states in describing machine intelligent and intelligent decision, planning, reasoning about action, and so on. We introduce an operator *Knows* to represent robot's mental states involving knowledge.

Definition1 Let ϕ be a first order statement, IKB is the internal knowledge base of the robot, then *Knows* (Robot, φ) denotes " Robot knows φ", and *Knows* (Robot, φ) is interpreted in L_{MK} as

Knows (Robot, φ) if and only if φ ∈ IKB.

Definition1 indicates that a robot knows and only knows the knowledge in its internal knowledge base IKB. Relationship of sensing data, internal knowledge and mental states are showed in Figure 3.

Sensing data	IKB	mental states
< BOOK, b, YES >	BOOK(b) is true	*Knows* (Robot, BOOK(b))
< BOOK, d, NO >	BOOK(d) is false	*Knows* (Robot, DESK(d))
< DESK, d, YES >	DESK(d) is true	*Knows* (Robot, ON(b, d))
< ON, b, d, YES >	ON(b, d) is true	

FIGURE 3 Relationship of sensing data, internal knowledge and mental states

3.3 IKB AND MACHINE KNOWLEDGE

The so-called "machine knowledge" refers to the knowledge acquired by robot systems in the following way. A robot uses its sensors to sense the external environment, and the sensors transfer the external states (environment) to the robot's memory in the form of sensing data, then the robot converts the data into knowledge through the system mechanisms, and the knowledge is stored in the robot's knowledge base, forming its own internal state(for environment awareness). Robots can autonomously use their knowledge when planning and making decision without any external intervention. Since the process of acquiring *knowledge in IKB is finished autonomously by robot system.* So robot's internal knowledge can be considered as knowledge of the machine. The reasons are as follows.

- *each sensor is a* independent subsystem and *can work in an autonomous way. For example, if the robot starts the sensor* $\overline{BOOK}(x)$ to work on object a, then $\overline{BOOK}(a)$ automatically outputs "YES" / "NO".
- Since sensors are part of the robot system, the system can control and manage these sensors. Particularly, the system remembers sensors' name. So when $\overline{BOOK}(a)$ returns "YES" to the system, it can get sensing data < BOOK, a, YES > according to sensor's name "BOOK", object "a" and output value "YES". This process is also completed in the robot's system.
- L_{MK} is a formal system and the semantics of formula in L_{MK} is based on sensing data. So the system can interpret formula without relying on the designers and pre-designed models. To convert sensing data < BOOK, a, YES > to knowledge "a is a book" (or predicate formula BOOK(a)) is easy in L_{MK}.
- According to definition1, robot's mental states come from IKB is clear and determined. Robots can use their knowledge to design planning and perform actions without interference from the external operators.

4 An application example of the logical framework

In this section, we illustrate an application of the logical framework. A hypothetical scenario is as follows: there are 4 people, a book, a desk, a bookshelf, an office, a laboratory and a library in the environment. The book was on the desk in the office initially. Then several events happened.

- **The first time:** Person 1 walked into the office and saw a book on the desk. He didn't touch the book and then left the office;
- **The second time:** Person 2 walked into the office and saw the book on the desk. Next, he took the book to the laboratory and put the book on the bookshelf, and then left the laboratory;
- **The third time:** Person 3 walked into the laboratory and saw the book on the bookshelf, then he took the book home.
- **The fourth time:** Person 4 sent a message to Person 1, Person 2 and Person 3: "Please send the book to the library if you know where the book is."

Here, we suppose that any two of them did not exchange information each other. We want to know what actions they will take. In general, the following actions would be appropriate.

(1) Person 1 will go to the office, because he knows the book is on the desk in the office;

(2) Person 2 will go to the laboratory, because he knows the book is on the bookshelf in the laboratory;

(3) Person 3 will takes the book in his home and send it to the library.

We will represent the above events using the formal language of L_{MK}. For the sake of simplicity, we only describe formally the putout values of sensors, sensing data and internal knowledge, and describe actions and situation calculus in informal language.

The initial situation S_0: {ON(b, d), b = book, d = desk}.

- **Event 1:** robot 1 walks into the office and starts the sensor $\overline{BOOK}(x)$ and $\overline{DESK}(x)$ to work on object *b* and *d* respectively, and robot 1 also starts the sensor $\overline{ON}(x,y)$ to work on *b* and *d*, then $\overline{BOOK}$(b) putouts "YES", $\overline{BOOK}$(d) putouts "NO"; $\overline{DESK}$(b) putouts "NO", $\overline{DESK}$(d) putouts "YES"; $\overline{ON}$(b, d) putouts "YES". Next, robot 1 get sensing data < BOOK, b, YES >, < BOOK, d, NO >, < DESK, b, NO >, < DESK, d, YES >, < ON, b, d, YES >. Next, robot 1 acquires internal knowledge BOOK(b), DESK(d), ON(b , d). Finally, Robot 1 leaves the office. Thus, we have situation S_1:
- {ON(b, d), b = book, d = desk, s = bookshelf, h = home; Knows (Robot 1, BOOK(b)), Knows (Robot 1, DESK(d)), Knows (Robot 1, ON(b, d))}.
- **Event 2:** robot 2 walks into the office and starts the sensor $\overline{BOOK}(x)$ and $\overline{DESK}(x)$ to work on object *b* and *d* respectively, and robot 1 also starts the sensor $\overline{ON}(x,y)$ to work on *b* and *d*, then $\overline{BOOK}$(b) putouts "YES", $\overline{BOOK}$(d) putouts "NO"; $\overline{DESK}$(b) putouts "NO", $\overline{DESK}$(d) putouts "YES"; $\overline{ON}$(b, d) putouts "YES". Next, robot 2 get sensing data < BOOK, b, YES >, < BOOK, d, NO >, < DESK, b, NO >, < DESK, d, YES >, < ON, b, d, YES >. Next, robot 2 acquires internal knowledge BOOK(b), DESK(d),

ON(b , d). Next, Robot 2 takes the book to the laboratory and put the book on the bookshelf, and then leaves the laboratory. At this time, Robot 2's sensing data and internal knowledge needs to be updated. Finally, Robot 2 acquires internal knowledge BOOK(b), DESK(d), BOOKSHELF(s), ON(b, s). Thus, we have situation S_2:

- {ON(b, s), b = book, d = desk, s = bookshelf, h = home; Knows (Robot 1, BOOK(b)), Knows (Robot1, DESK(d)), Knows (Robot 1, ON(b, d)), Knows (Robot 2, BOOK(b)), Knows (Robot 2, DESK(d)), Knows (Robot 2, BOOKSHELF(s)), Knows (Robot 2, ON(b, s))}.
- **Event 3:** robot 3 walks into the laboratory and starts the sensor $\overline{BOOK}(x)$ and $\overline{BOOKSHELF}(x)$ to work on object b and s respectively, and robot 3 also starts the sensor $\overline{ON}(x, y)$ to work on b and s; then $\overline{BOOK}$(b) putouts "YES", $\overline{BOOK}(s)$ putouts "NO"; $\overline{BOOKSHELF}$(b) putouts "NO", $\overline{BOOKSHELF}(s)$ putouts "YES"; $\overline{ON}(b, s)$ putouts "YES". Next, robot 3 get sensing data < BOOK, b, YES >, < BOOK, s, NO >, < BOOKSHELH, b, NO >, < BOOKSHELH, s, YES >,, < ON, b, s, YES >. Next, robot 3 acquires internal knowledge BOOK(b), < BOOKSHELH, s, YES >, ON(b , s). Next, Robot 3 takes the book to home. At this time, Robot 3's sensing data and internal knowledge needs to be updated. Similar to the previous step, Robot 3 finally acquires internal knowledge BOOK(b), BOOKSELF(s), IN(b, h). Thus, we have situation S_3:
- {ON(b, s), b = book, d = desk, s = bookshelf h = home; Knows (Robot 1, BOOK(b)), Knows (Robot 1, DESK(d)), Knows (Robot 1, ON(b, d)), Knows (Robot 2, BOOK(b)), Knows (Robot 2, DESK(d)), Knows (Robot 2, BOOKSHELF(s)), Knows (Robot 2, ON(b, s)), Knows (Robot 3, BOOK(b)), Knows (Robot 2, BOOKSHELF(s)), Knows (Robot 2, IN(b, h))}.
- **Event 4:** Robot 4 sends a message to Robot 1, Robot 2 and Robot 3: "Please send the book to the library if you know where the book is". Robots react according to their own knowledge.

✓ Robot 1 goes to the office according to its individual knowledge
Knows (Robot 1, ON(b, d));

✓ Robot 2 goes to the laboratory according to its individual knowledge
Knows (Robot 2, ON(b, s));

✓ Robot 3 takes the book from his home to the library according to its individual knowledge
Knows (Robot 2, IN(b, h)).

It is easy to see that Robot 1, Robot 2 and Robot 3 all make a correct decision. And all people would do it in such a way.

5 Conclusion

In this paper, we propose a logic framework L_{MK} for describing machine knowledge. The syntax of L_{MK} is an extension of situation calculus action theory and the semantics of L_{MK} is based on sensing data. Compared with the possible world accessibility relations or situation acessibility relations, the proposed semantics has a much stronger ability to describe the autonomy of robots. We introduce a formal method to represent sensors, sensing data and knowledge in L_{MK} and design a mechanism converting sensing data into knowledge and automatically updating the internal state of robots. We also provide the an application example of the logic framework to show the autonomous performance of robots describing in L_{MK}. Our logical approach does not involve possible world models in modal logic. The main contribution of our work is to present a new approach for researching machine intelligence, developing along the direction of "machine code–machine data–machine knowledge machine intelligence". On this basis, We will further study machine intelligence including "machine belief", "machines emotion", machine consciousness etc.

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