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Intelligent Decision Model for Home Robot Based on Structured and Unstructured Data Processing

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***Abstract*— In order to enhance the user's service experience and help the robot to make more intimate service decisions, this paper proposes a service task cognition and decision model based on structured and unstructured data processing. Firstly, all kinds of information mentioned in user instructions are extracted through natural language processing, including object information, namely structured data and environment information, namely unstructured data. For structured data, it is mapped to the predefined ontology knowledge base to obtain its location attributes and state attributes, and then obtain service instructions. Adaptive fuzzy Petri net (AFPN) is constructed based on fuzzy rules of temperature, humidity and other environmental information. The unstructured data is taken as the input parameter of AFPN, and the service instruction deduced as the output. Then, according to the user's needs, the network weight can be continuously adjusted. If the user does not mention the environmental information, the environment information is periodically detected by the sensor, and the service instruction reasoning of the unstructured data is performed. Finally, back propagation neural network (BPNN) is introduced to combine the service inference of two kinds of data to eliminate the heterogeneity of different service instructions. Experimental results show that the model can provide different personalized services for users' preferences.**

***Index Terms*— Natural Language Processing, Structured and Unstructured Data, Ontology, AFPN, BPNN**

I. Introduction

The decision-making process is ubiquitous in human life and work. Human beings face different choices every day and make decisions through reasoning and psychological processes [1]. Similarly, how to better understand the user's command intentions in daily life and how to provide users with more intimate services, require intelligent robots to continuously learn decisions, and then judge and implement the corresponding service tasks. In some cases, user's instruction data is very clear and logically simple. Such data is easy to write to the database, so they're called structured data [2]. The problem of processing structured data is called well-structured problem [3], and the decision of robots to solve well-structural problems is relatively easy to implement. For instance, in some practical examples, motion instructions can be communicated by receiving input data at the home automation system and processing the input data to obtain action instructions [4]. The smart home environment decision model [5] uses a hidden Markov model (HMM). The model provides decision support by analyzing residents' daily life data and predicts residents' family activities. Alireza and Kathleen [6] help clinicians determine if a patient is abnormal by analyzing household daily life data. They identify chronic health conditions and unexpected health events by identifying abnormal data. However, analyzing the data to predict the results lacks the flexibility to adapt to the changes of users. Van Dang and Tran [7] apply Soar's cognitive agents to home service robots, making appropriate decisions based on family location and health. Costa and Castillo [8] build an intelligent agenda manager and intelligent monitoring framework through real-time monitoring of sensors. The framework is capable of detecting activity in the elderly, scheduling equipment and assisting robots to make decision intelligence, and provides fall detection. However, the data they use for decision-making is relatively single, which cannot cover users' daily life more comprehensively.

Generally, people's demand expression is fuzzy, which leads to many problems without an accurate answer, the data thus obtained is unstructured. This makes it necessary for robots to output accurate decisions in continuous improvement. Such problems are called ill-structured problems. In this context, Zhou and Luo [9] propose reinforcement learning to achieve practical questions and answers, using real users to interact with robots, but this method requires a lot of learning time and human resources. Gesture interaction and voice interaction are popular ways for human-robot interaction. Wang and Li [10] propose to introduce the gesture interaction decision model into the human-robot interaction process. The service decision of the robot is realized by formulating the meaning of the person's gesture. Chahuara and Pedro [11] propose a combination of speech analysis and context awareness modules to help users make more comfortable decisions. However, both gestures and voice require the user to make a service request. Emotion is also important in human decision making. If emotional reasoning is added to the humanoid robot and the events are analyzed hierarchically, some complex decision problems can be solved [12]. Shi and Li consider the subjective factors of users, but ignore the influence of the objective environment on users.

No matter it is a well-structured problem or an ill-structured

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problem, if the robot can be viewed from the user and understand the direct and hidden needs of the user, a more harmonious human-robot interaction can be achieved. Therefore, this paper proposes a self-aware cognitive decision model for home robot based on structured and unstructured data processing. At first, the structured and unstructured data are extracted by processing the user's commands. Then, we build an ontology knowledge base containing class, object properties and data properties, and the structured data obtained through natural language processing can be directly queried in the ontology base. Next, the membership function is set and the environment information is blurred according to the membership function. On this basis, combined with the predefined fuzzy rule base, AFPN is used to analyze and identify the unstructured data, and the service conclusion was obtained. Finally, combined with the pattern recognition ability of BPNN, structured data and unstructured data are trained at the same time to get a more comprehensive service conclusion.

II. The Intelligent Decision Model

The service cognitive decision-making model structure is shown in Fig. 1. As shown in the figure, when the user issues service instructions, the information contained in the instruction is divided into structured data and unstructured data by using natural language analysis technology. For structured data, direct service task reasoning is performed using operational attributes, location attributes, etc. of individual objects already in the ontology database. For unstructured data, the corresponding data is blurred according to its membership function, and the extended service instruction is obtained by AFPN. Finally, combined with two types of service instructions, BPNN trains a more comprehensive service decision information to the robot.

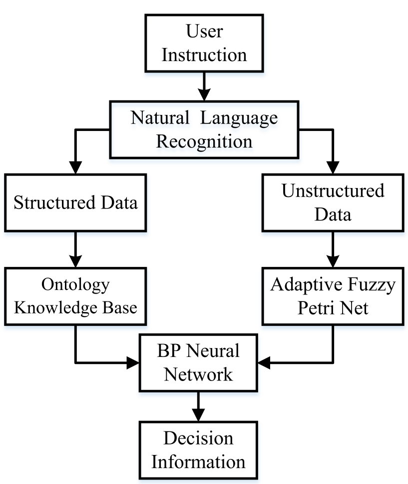


Fig. 1. Decision-making model flow chart

III. Data processing and Structured Data Reasoning

A. Data Extraction and Classification

Regarding the extraction and classification of data, we first build a keyword base. Nouns such as TV and book are classified as direct operation keywords, which are used as structured data [13], adjectives such as cold and bright are classified as indirect operation keywords, which are used as unstructured data. By analyzing the user's command, Levenshtein distance matching words were used to extract the keywords. In order to increase the recognition accuracy, increase the keyword ranking, equivalent, transpose, word split and other processing methods. The keywords involved will be added to the MySQL database, easily to increase, delete and query the data.

B. Building Ontology Knowledge Base

Ontology is an accurate description of the shared conceptual model and plays an important role in the reuse and sharing of knowledge [14]. Based on the OWL(Web Ontology Language) system language, this paper constructs the ontology knowledge base of the home environment by using the ontology development tool protg [15]. The base contains ore than 300 operating objects and 120 environmental objects. Each object has its object properties and data properties, which can facilitate the robot's positioning and operation of the object. The structure is shown in Fig. 2. The solid lines in the Fig. 2 represent the inclusion relationships, the dashed lines indicate that the environmental objects have active and passive object properties and data properties, and the operational objects also have active and passive object properties and data properties.

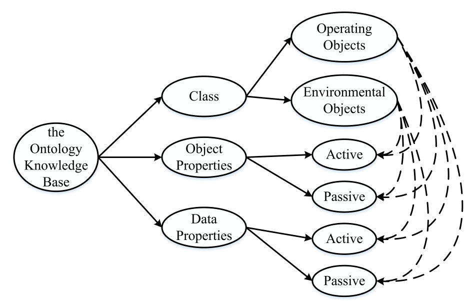


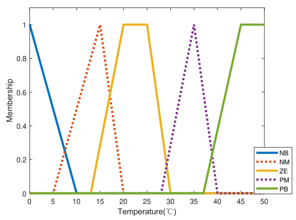
Fig. 2. Structure diagram of the ontology base

IV. Unstructured Data Reasoning

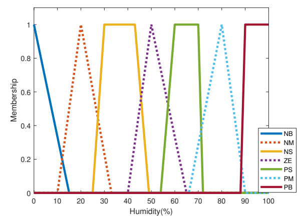
The fuzzy system is suitable for describing the ambiguity in natural language and human thinking. The rule-based fuzzy system has been widely used due to its versatility, such as image processing, target recognition, disease diagnosis, etc[16,17,18,19]. The construction of fuzzy logic mechanism can be divided into 3 modules: membership function, fuzzy reasoning mechanism and building AFPN.

A. Define Membership Function

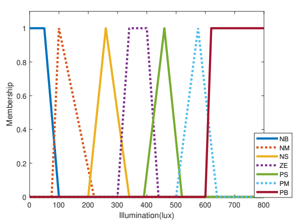
We analyze and define fuzzy operators with universal environmental variables, including temperature, humidity, illumination, etc., and divide the fuzzy operator into seven states, including very high (PB) and high (PM), slightly high (PS), moderate (ZE), slightly lower (NS), lower (NM) and very low (NB). The membership function of time and space is also defined. The membership functions are as shown in Fig. 3(a)-(d).



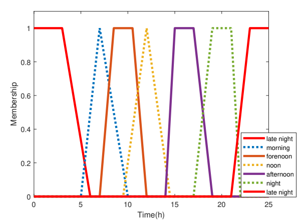
(a) Temperature membership function



(b) Humidity membership function



(c) Illumination membership function



(d) Time membership function

Fig. 3. Membership function image representation

AFPN applies 4 input parameters, namely temperature, humidity, illumination and time. The X coordinate of the coordinate point in the figure represents the exact environmental value, and the Y coordinate represents the membership degree corresponding to X in a fuzzy boundary. As shown in Fig. 3(c), the fuzzy process of the "fit" illumination can be expressed as (1).

$$Y = \begin{cases} 0 & X < 300 \\ \frac{1}{40}(X-300) & 300 \le X < 340 \\ 1 & 340 \le X < 400 \\ -\frac{1}{40}(X-440) & 400 \le X < 440 \\ 0 & X \le 440 \end{cases} \quad (1)$$

B. Definition of Adaptive Fuzzy Petri Net

A typical AFPN is shown in figure 4. The adaptive fuzzy Petri net is defined as a model containing 9 tuples [20],

$$AFPN = (P, T, D, I, O, \alpha, \beta, Th, W) \quad (2)$$

$P = \{P_1, P_2, \cdots, P_n\}$, where P represents the places, indicating conditions, resources, waiting queues and channels, etc., T represents the transition, indicating events, actions, statement execution and message transmission or acceptance, etc., where $T = \{t_1, t_2, \cdots, t_m\}$. $D = \{d_1, d_2, \cdots, d_n\}$, where D represents the set of propositions. I is the input function, which is the mapping to the input places, and O is the output function, which is the mapping to the output places. α and β are correlation functions, which respectively represent the mapping of a place from the true value and the mapping of a place to the set of propositions. Their range of values is [0, 1]. The value range of Th is also [0, 1]. Th is the threshold defined for the transition node, $Th = \{\lambda_1, \lambda_2, \cdots, \lambda_m\}$. W_I is a mapping of input weights from 0 to 1 to each arc of the kth order, and W_O assigns output weights from 0 to 1 to each output arc. And

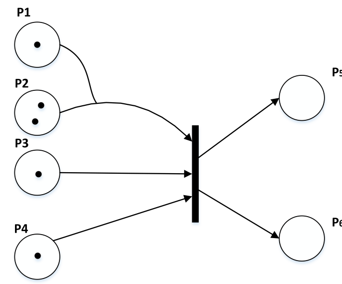


Fig. 4. A typical adaptive fuzzy petri nets

$$P \bigcup T \bigcup D = \phi \quad (3)$$

C. Fuzzy Production Rules

The fuzzy production rule describes the fuzzy relationship between multiple propositions, which is the fuzzification of the knowledge rules from the premise to the conclusion. Generally, the form of fuzzy production rules can be divided into three types:

TYPE 1:IF d_i THEN d_j (λ, w_I, w_O).

TYPE 2:IF d_1 AND d_2 AND $\cdots$ AND d_m THEN d_j $(\lambda_1, \lambda_2, \cdots, \lambda_m; w_{I1}, w_{I2}, \cdots, w_{Im}; w_O)$.

TYPE 3:IF d_1 OR d_2 OR $\cdots$ OR d_m THEN d_j $(\lambda_1, \lambda_2, \cdots, \lambda_m; w_{I1}, w_{I2}, \cdots, w_{Im}; w_O)$.

D. Improved Fuzzy Reasoning and Learning Algorithm for AFPN

Since the tolerance of different users to different environmental variables is different, the true value of the conclusion variable will change after applying the fuzzy inference algorithm. Service requirements are the final output of the network. The robot needs to improve the membership function of the membership function according to the user's response, in order to realize the personalized service in the true sense. At this time, the weight parameter needs to be adjusted according to the new true value of the output places [21]. Therefore, an algorithm Least mean square (LMS) is used for updating the weights, the expression is:

$$w(n+1) = w(n) + \mu p(n)e(n) \quad (4)$$

where $w(n)$ represents the weight value of the n, $w(n+1)$ represents the weight value of step n+1, and μ is the learning rate parameter. The value range of μ is [0, 1], and the larger μ is, the faster the update will be. $p(n)$ represents the value of the place at step n, and $e(n)$ is the difference between the output and the objective function. The LMS algorithm is simple to program, and it is an independent robust model for external disturbances. Define an operation:

$$[a_1, a_2, \cdots, a_n] \uplus [b_1, b_2, \cdots, b_n] = [a_1 \cdot b_1, a_2 \cdot b_2, \cdots, a_n \cdot b_n] \tag{5}$$

The improved AFPN fuzzy inference and learning algorithm is as follows, where $N(x)$ represents the number of x, T_{en} represents the activated transition, and A_I represents the input arc. $\Phi_I(n) = \alpha(P_O) \uplus w(n)$.

Algorithm 1 The fuzzy reasoning and learning algorithm

Input: The input places' true values $\alpha(P_I)$ and the original weights $w(n)$

Output: The output places' true values $\alpha(P_O)$

```
Build input places P_I.
Build initially enabled transitions T_en.
while t_i ≠ σ do
    if Φ_I > Th_I(n) then
        if N(T_en) = 1 and N(A_I) = 1 then
            α(P_O) = v_O · Φ_I(n)
        if N(T_en) = 1 and N(A_I) > 1 then
            α(P_O) = v_O · max[Φ_I(n)]
        if N(T_en) > 1 then
            α(P_O) = max[v_O · Φ_I(n)]
        else
            break out
    N(T) = N(T) − N(T_en)
    calculate the input weights as Eq.(4)
return result
```

V. Cognitive Decision Based on BPNN

AFPN can describe ambiguities in human thinking, but it is impossible to make comprehensive inferences for undefined situations, while BPNN is fully connected and can realize the ability of learning, association and memory through its network structure. Combining the two types of data inference using AFPN provides complementary advantages.

A. Collecting and Processing Sample Data

As the input layer of BP neural network, sample data needs to encode the language of words into numerical form, which is convenient for neural network training. In order to facilitate understanding, this paper slightly improved the 0-1 encoding method [22] to digitize the relevant data. The original collected data is shown in Table I, and the processed data is shown in Table II. In order to reduce the complex dimensions of the data space, the model defines the smart home mentioned in the service as five forms, no effect as "0", turn on as "1", turn off as"2", turn up as"3" and turn down as "4". The collected data is stored in the MySQL database, which is convenient for data to store, read and change.

TABLE I
PARTIAL RAW SAMPLE DATA

Environmental			Time	Service
Temperature	Humidity	Illumination		
NB	NB	NB	Morning	turn_on_TV
NM	NM	NM	Forenoon	turn_up_humidifier
ZE	NS	NS	Noon	turn_off_light
PM	ZE	ZE	Afternoon	open_windows
PB	PS	PS	Night	open_air_conditioner
	PM	PM	late_at_night	
	PB	PB		

TABLE II
0-1 ENCODING SAMPLE DATA

Environmental			Time	Service
Temperature	Humidity	Illumination		
10000	1000000	1000000	100000	10000
01000	0100000	0100000	010000	03000
00100	0010000	0010000	001000	00200
00010	0001000	0001000	000100	00010
00001	0000100	0000100	000010	00001
	0000010	0000010	000001	
	0000001	0000001		

B. Construction of BPNN

The training model of BPNN is shown in Fig. 5. In the fuzzy model, BPNN uses evolutionary computation algorithms to generate, select and optimize fuzzy control rules. BPNN uses its network full connectivity to assist AFPN in reasoning, and finally achieves defuzzification and output service decision.

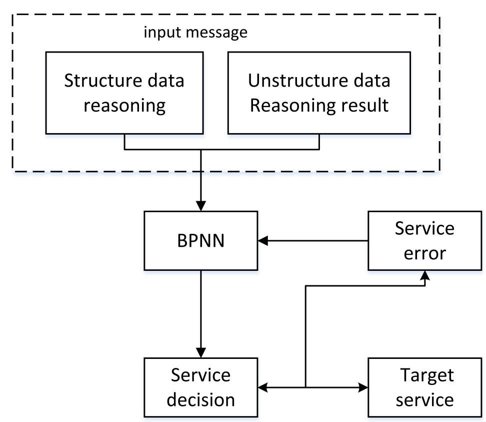


Fig. 5. Neural Network Training Model

VI. Experiment and Analysis

A. Data Classification

For user's service requests, the algorithm matching keywords are mainly used to extract keywords and classify keywords. For the possible errors in word recognition, Levenshtein algorithm is chosen to match words in this paper. The Levenshtein distance [23] is a string measure that calculates the degree of difference between two strings. You can think of the Levenshtein distance as the minimum number of times you need to edit a single character (such as modify, insert, delete) to change from one string to another. In the word matching experiment setup, if the Levenshtein distance is less than 3, then the two words belong to the same word. The experimental results are shown in the Table III. Due to the small amount of unstructured data, the accuracy is slightly higher than that of structured data. The resolution of combining the two can reach 80.77 %.

TABLE III
SWRL RULES CLASSIFICATION

Keyword category	Number	Correct rate(%)
Structured	210	78.53
Unstructured	73	87.26
Amount	283	80.77

B. An Instance of Structured Data Reasoning

As shown in the experimental results in Figure 6, when the structured data is detected to be "TV", the location of the TV can be queried through the ontology knowledge base to be in "living_room" and the operation required is"turn_on". Since this part of reasoning mainly relies on pre-definition, there is no error problem.

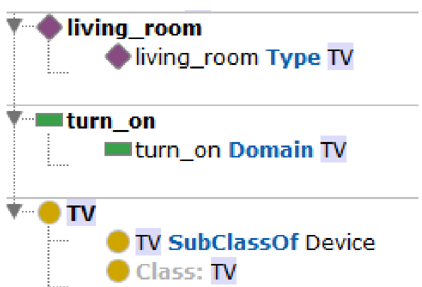


Fig. 6. Ontology decision experiment

C. An Instance of AFPN

As shown in the experimental results in Figure 5, when the user issues the "Watch TV" command, it automatically obtains environmental information and spatio-temporal information, temperature 18 °C, humidity 71 %, brightness 280 lux, time 21:53:37, TV in " living_room". According to the definition of membership function, the membership degrees of temperature at this moment are [0,0.4,0.7143,0,0], respectively, and the membership degrees of humidity are [0,0,0,0,0.5,0.3571,0], respectively. The membership degrees of illumination are [0, 0, 0.75, 0, 0, 0, 0], and the membership of time is [0, 0, 0, 0, 0.3, 0.7]. Therefore, reasoning through AFPN, the result is [0, 0, 0.63, 0.71, 0], because the third and fourth terms are greater than 0.5, do the following decision informations:turn on lights and open windows.

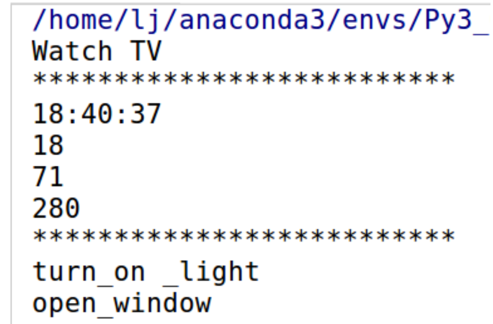


Fig. 7. AFPN decision experiment

D. BP Neural Network Cognitive Decision Experiment

This paper selects a database containing time and space information and environmental information collected at the beginning of the experiment, totaling 340. Choose 70% of the data for the training set, 15% for the validation set, and 15% for the test set. According to the structured data reasoning results and unstructured data reasoning results, the input layer of the BP neural network is set to 32. This includes location(5 species), state(2 sepcies), temperature(5 species), humidity(7 species), illumination(7 species) and time(6 species). The output layer is 5, including services as Table II. After several tests, when the hidden layer node is set to 10, the iteration time is shorter, only 1 seconds.

As shown in Fig. 8, the mean square error (MSE) of the test set can reach 8.22573e-14, close to 0, showing a close correlation between output and target? and the best validation performance is 0.0040764 at epoch 14.

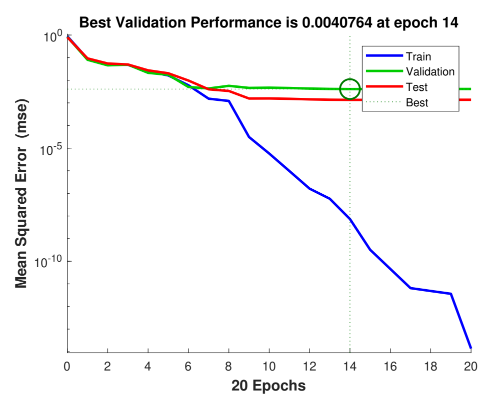
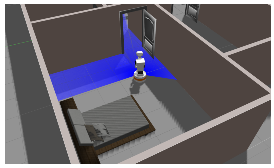


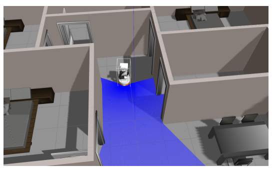
Fig. 8. The Mean Square Error

The model was applied to a previously built home environment based on the TIAGO simulation platform. The platform developed the target recognition and path navigation module to verify the feasibility of the home robot cognitive decision system. The experimental results are shown in Fig. 9. The experimental results verify the following process: After the robot receives the "Watch TV" command, it moves from the bedroom to the corridor and then to the TV in the living room. The blue line in the upper left corner indicates the route of action.

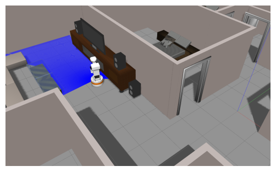
(a) The action route



(b) The bedroom



(c) The corridor



(d) The living room

Fig. 9. Robot motion track

VII. Conclusion

This paper establishes a self-aware cognitive decision model for home robot service based on structured and unstructured data processing. The model takes into account both structured and unstructured information, making up for the one-sided problem of previous work considerations. After the user instruction is received by the model, the instruction is divided into structured data and unstructured data through the natural language processing system. On the one hand, the structured data is queried through the pre-built ontology database to obtain its location attributes and state attributes, and then the operation instructions are obtained. On the other hand, AFPN is used to process unstructured data, and operation instructions are obtained through membership function and fuzzy rules. At the same time, other unstructured data not mentioned are also processed to obtain operation instructions. Finally, the two types of processing processes were handed over to BPNN to learn the combination of user commands or non-existent environment variables, which improved the accuracy of service decision. Existing solutions are not yet able to fully cover the needs of home users, and will be supplemented and improved in the next step.

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