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CLEANING ROBOT OPERATION DECISION BASED ON CAUSAL REASONING AND ATTRIBUTE LEARNING*

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Abstract—**In order to improve the operation ability of cleaning robots, this paper proposes a decision method for cleaning robot's operation mode. Firstly, we use the hierarchical expression ability of deep network to obtain the attributes of garbage such as state, shape, distribution, size and so on. Then the causal relationship between the attributes and the operation modes can be built by using joint learning of association attributes with depth network model and causal inference. Based on this, a fuzzy inference decision network is designed. With the help of causal analysis, the structure of the decision model is greatly simplified. Compared with conventional fuzzy neural networks, the total parameters of the model are reduced by 2 / 3. The method proposed in this paper imitates the way that human dispose of different types of garbage and has good interpretability. The experimental results verify the effectiveness of the proposed method.**

I. INTRODUCTION

Although the household cleaning robots has been industrialized massively, there are still many unsolved problems in practical application, two of which are weak intelligence and single cleaning mode. For example, the household cleaning robot usually only has merely two operation modes, sweeping and erasing, which can only be used to clean small objects such as dust and debris. Besides, it is unable to identify the garbage without visual perception ability. Therefore, the robot can't take proper cleaning mode for different garbage. In a word, the intelligent level and capability of the existing cleaning robots are far from the human beings.

In order to improve the level of intelligence of the cleaning robot, it may be useful to observe and analyze the behavior of human beings. In the process of cleaning, people usually adopt different operation modes according to the characteristics of garbage. For example, liquid is usually removed by erasing. Small and solid garbage such as paper scraps and melon shells are cleaned with sweeping mode. Grabbing mode is suitable for cleaning larger bottles and cartons. For plastic bags, the best way to clean is to perform adsorption mode. According to the above analysis, it is necessary to equip the cleaning robot with vision sensors and multiple cleaning operation modes to improve the working ability.

The aim of this paper is to realize that the robot can judge the type of garbage and take appropriate operation mode autonomously. It is noted that the problems of identification and the analysis of attributes of garbage belong to the visual perception. While the decision for operation modes belong to cognition problem. Because of the huge semantic gap between them, it is obviously difficult to directly construct a reasoned decision-making model based on garbage images. On the contrary, Human's reasoning and decision-making process is more reasonable and interpretable. When humans making inference decisions, they will first obtain various attributes of the object through observation, and then use rules and obtained knowledge to reason. Similarly, in order to avoid constructing an intuitive reasoning model from image to decision directly, we will realize the robot's independent decision-making of the garbage cleaning mode in two stages, respectively from image to attribute (visual perception), and from attribute to decision (cognitive inference). The former solves the attribute learning problem and the latter solves the problem of cognitive decision-making. Common sense tells us that the main factors influencing the decision-making of the cleaning model are the shape, state, distribution and size of garbage. Therefore, we will firstly use the hierarchical expression ability of deep network to obtain the attributes of garbage such as state, shape, distribution, size and so on. Next, the causal relationship between the attributes and the operation modes can be built by using causal inference. And a fuzzy inference network for operation mode decision can be designed.

The main contributions of this paper are reflected in the following three aspects: (1) The proposed decision-making of the cleaning model in this paper is very similar to human decision-making behavior, which combined perception and cognition behaviors. Thus, the proposed model has good interpretability. (2) The use of two stages processing greatly reduces the difficulty of the problem. It makes it possible to obtain a good autonomous decision-making of cleaning model. (3) The introduction of causal learning technology is conducive to the joint learning of attributes and the design of fuzzy inference network.

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II. Brief Review of Attribute Learning And Causal Resaoning

A. Attribute Learning

Visual attributes, such as color, shape and components, are the basic characteristics of objects that can be perceived by human being. These visual attributes play an important role in understanding and describing objects. Human beings can easily describe everything with language, while computers do it based on data. There is a "semantic gap" between the underlying features and the high-level semantics for computers [1]. As the visual attribute is a description of the layer semantics in the image and can be understood by both humans and machines. V Ferrari and A Zisserman [2] proposed the concept of "visual attributes" to solve the "semantic gap". A Farhadi et al. [3] furtherly promoted visual attribute research in article "Describing Objects by their Attributes" at the CVPR conference. The purpose of attribute learning is to establish the connection among low-level features, attributes and high-level semantics. The traditional strategy of attribute learning is to train a classifier corresponding to each attribute. Early attribute learning mostly relied on hand-designed features such as SIFT, Gabor, and HOG. Considering the excellent performance of deep convolutional neural networks (DCN) in tasks such as image classification, it can play an important role in attribute extraction and learning. For example, Razavian [4] and Donahueet et al. [5] use the feature representation learned by ImageNet to train the process of attribute classification.

The representation of attributes has two types, i.e., discrete attributes and continuous attributes. Discrete binary attribute can only describe whether the object has or does not have a certain attribute, which is obviously not satisfied with the description of some indistinguishable attributes. In response to this problem, the concept of “relative attributes” was introduced by Kristen Grauman [6] who proposes to rank the attributes and use the value of the score to represent the strength of the attribute, so as to determine the relative differences between the attributes of different images.

There are not only correlations but also obvious differences between visual attributes. Modeling correlations and heterogeneity is an important research content for efficient and robust attribute learning. In early studies, these correlations between attributes have not been fully utilized, such as the indirect attribute prediction model (IAP) and direct attribute prediction model (DAP) proposed by Lampert et al[7]. As an improvement, a multi-task learning-based joint attribute learning method has been developed recently. As an example, a multi task face attribute learning model for face attribute analysis is established in [8]. Because it can not only ensure the sharing of underlying features, but also meet the deliberate fine tuning of attributes, the multi-task attribute learning is usually better than single task attribute learning.

Existing attribute learning has been widely applied in the fields of face attribute analysis, image classification, visual retrieval, zero-shot learning and transfer learning. The decision-making problem of cleaning operation mode studied in this paper has not been reported publicly. When analyzing garbage attributes, this paper mainly considers four attributes: state, shape, distribution and size. Among them, the first three attributes belong to the disordered nominal feature, and the size attribute belongs to the ordered quantitative feature. For this reason, the attribute features are divided into two groups in research, and the fine-grained training is performed separately at the fully connected layer at the back end of the deep network.

B. Causal Reasoning

Causality reflects the objective process of the interaction of various factors between things. In recent years, with the research results of causal inference constantly recognized by the academic community, this field is becoming a research hotspot. The successive publication of some causal works has a wide and far-reaching impact on the development of causality [9-14].

Causal network, which can be used to analyze the probability through the variables among things, is a popular tool for inferring the relationship between variables in the study of causal reasoning. Causal inference algorithms are generally divided into two stages: causal skeleton learning and causal direction inference. Common algorithms include: scoring-based search methods, constraint-based methods, causal function model-based methods and hybrid-based methods. The principle of search method based on score is to construct a causal Bayesian network structure for all network nodes according to a certain search strategy and scoring mechanism [16]. One of the typical algorithms is K2. Constraint-based algorithms can be understood as conditional independence testing methods. As early as 1990, Peter et al. Proposed the PC (Peter-Clark) algorithm [17] and the IC (Inductive Causation) algorithm [18]. In 1995, Peral et al. [19, 20] proposed the Structural Equation Model (SEM) and Potential Outcome. Later he proposed the Structural Causal Model (SCM). The core of the framework model of potential results is to compare the results of the subjects who received the intervention with those who did not. Li Wenzhao [21], also gives a systematic, comprehensive and in-depth introduction to the potential result model of causal reasoning. Philosophers also use the counterfactual framework of the potential result model of causal reasoning to study the philosophy of causal reasoning [22]. As an improvement of causal structural equation model, Shimizu et al. [23] proposed the Linear Non-Gaugesian Acyclic Model——LiNGAM (Linear Non-Gaugessian Acyclic Model) and its improvement——Direct LiNGAM model [24]. Zhang et al. [25] proposed the SICA (ICA with Sparse Connections) method. Janzing et al. [26, 27] proposed an Information-Geometric Causal Inference method (IGCI). As a new method for distinguishing binary causality, IGCI is developed based on the assumption of independence between input distribution and causality mechanism to express the orthogonality of information space.

Using the Constraint-based causal reasoning algorithms, the causal framework can be constructed quickly, and then the direction of causal network can be inferred preliminarily. However, its problem is that it can't recognize Markov equivalence class. In contrast, the method based on causal function model can solve this problem. The hybrid method is just based on the combination of constraint method and causal function model. Cai et al [28] proposed SADA framework. This method adopts the strategy of splitting and merging, and uses the causal network of local sparsity structure, which can accurately determine the causal variables in the case of high dimension and low sample. Zhang et al [29] proposed a causal inference algorithm CDHD for high-dimensional data. CDHD avoid the huge condition set of PC algorithm, and use the mixed direction recognition algorithm to infer the direction.

III. Analysis Of Garbage Attributes And Its Joint Learning

A. *Analysis Of Garbage Attributes*

Common sense shows that humans usually choose different cleaning modes according to the attributes of the garbage. Obviously, the main factors influencing the decision-making of the cleaning model are shape, state, distribution and size. In this paper, the state attributes mean solid or liquid; the shape attributes are non-flat or flat; the size attributes are divided into small, medium and large; the distribution attributes are distinguished with an organic whole (overall) or scattered. Correspondingly, we set four operation modes, namely sweeping, absorption, grasping and erasing mode. The sweeping mode is suitable for handling scattered, small, solid, and non-flat objects, such as melon shells, paper scraps, and glass fragments. The absorption mode is suitable for handling large flat solid objects, such as paper, plastic bags, etc. The grasping mode is suitable for handling medium- or large-size non-flat solid objects, such as cans, cartons, etc. Erasing mode is suitable for cleaning liquid objects (juice, tea, drinks) or dust.

All of the above-mentioned attributes can be obtained by visual sensors within a proper distance. We installed a Kinect camera on the top of the cleaning robot, which can obtain the RGB image and depth information of the object simultaneously. Through the depth information, we can judge the distance of the garbage. In order to ensure the reliability of the size, we stipulate that only the image obtained at a distance of 0.5m can be used for the analysis of size attributes. Moreover, a deep network model can be used to identify these garbage attributes with the help of attribute learning technology. After the attributes are extracted, the attribute information will be input to the subsequent fuzzy decision neural network for decision-making. The flowsheet for this process is shown in Fig. 1. Among them, the dotted blue box indicates the model training process, and the red box shows the actual working process of the robot. Fig. 2 is a schematic diagram of the overall composition of the model.

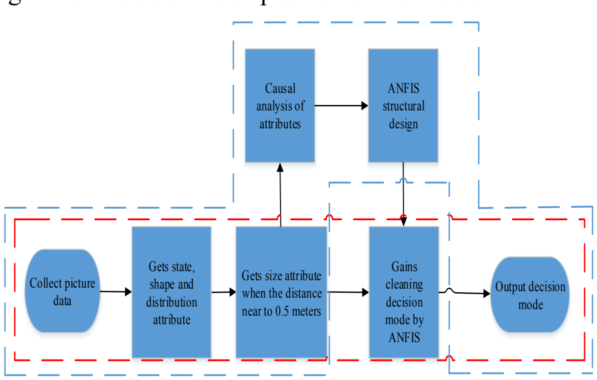


Figure 1. Cleaning robot working process

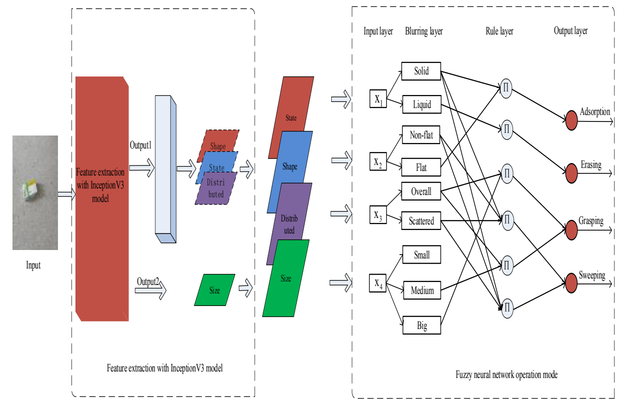


Figure 2. Schematic diagram of overall model composition

B. *Joint Attribute Learning*

Because multiple attributes are involved, and the correlation and heterogeneity between garbage attributes should be considered, therefore the study of garbage attributes in this paper will be a multi-task joint learning problem. In order to fully explore the correlation between attributes, the low-level features of deep network model can be shared learning, while the high-level features can be fine-tuned by the strategy of divide and rule to ensure the learning of heterogeneous attributes. Among the four attributes mentioned above, the state, shape and distribution belong to the overall appearance attributes of discrete objects, which are the disordered nominal attributes. Contrarily, the size attribute is continuous and orderly. For simplicity, the size attributes are discretized and expressed as three levels: small, medium and large. Thus the size attributes is discrete and orderly. In addition, the learning process of size attribute is separate from that of other attributes considering that the size attribute must be within a certain observation distance as mentioned earlier.

The network structure used to extract garbage attributes is shown in the Fig. 3, where the ImageNet image pre-trained Inception-v3 model is used as the backbone network for attribute learning. Through the shallow layer part of the network, we can get the texture, edge and other low-level features. As a shared feature layer, all attributes will be adjusted during learning to ensure the relevance of the learned attributes. With the increase of network depth and the enhancement of expression ability, high-level layer gradually learn abstract high-level semantic features. In order to extract specificities related to attributes such as state, shape, distribution, and size, we remove the output layer after dense_1 of the model and add output 1 and 2 to the full connection layer. The attributes of state, shape, and distribution are output from output 1, and the size attributes are output from output2.

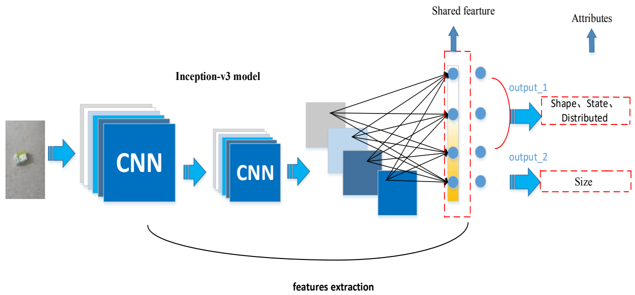


Figure 3. Inception-v3 based garbage attribute learning model

Suppose that there is a training data set containing N images, where each image has M attributes. The dataset is expressed as $D = \{\mathrm{X}, \mathrm{Y}\}$, $\mathrm{X} = \{X_i\}_{i=1}^{N}$, $Y = \{\{y_i^j\}_{j=1}^{M}\}_{i=1}^{N}$. The model shown in Fig. 3 can be trained by regularizing the minimum error loss function. The joint attributes learning model DMTL based on the multi-task is shown below:

$$\underset{W_c,\{W^j\}_{j=1}^{M}}{\arg\min} \sum_{g=1}^{2} \sum_{j=1}^{M^g} \sum_{i=1}^{N} \lambda^g L^g(y_i^j, F(X_i, W^g \circ W_c)) + \gamma_1 \Phi(W_c) + \gamma_2 \Phi(W^g) \quad (1)$$

where $F(\cdot)$ is the output function of the attribute prediction after the input X_i is processed by the deep network. $L^g(\cdot,\cdot)$ is the error loss function between the attribute output estimate and actual value y_i^j; $\Phi(\cdot,\cdot)$ is a regularization term, which is used to limit the complexity of weights. $\gamma_k, k=1,2$ is the regularization coefficient($\gamma_k > 0$). $W^g, g=1,2$ represents the weight of the subnet. W_c represents the weight of the shared network; $M^g, g=1,2$ represent the attributes of the corresponding task group, where $M^1 = \{\text{shape, state, distribution}\}$ $M^2 = \{\text{size}\}$. Because the selected attributes are discrete, we choose the cross entropy loss function as follows [30].

$$L^g = -\sum_{j=1}^{M^g} \sum_{i=1}^{N} \sum_{k=1}^{C^j} l(y_i^j, \hat{y}_i^{j,k}) \log p(\hat{y}_i^{j,k}) \quad (2)$$

where

$$p(\hat{y}_i^{j,k}) = \frac{e^{\hat{y}_i^{j,k}}}{\sum_{k=1}^{C^j} e^{\hat{y}_i^{j,k}}} \quad (3)$$

is the Softmax function. $\hat{y}_i^{j,k}$ is the possibility that the j-th attribute value output by the attribute learning network of the k-th discrete value. y_i^j is the real value. $l(a,b)$ is the label. When $a=b$, its value is 1; Otherwise, it is 0. The Inception-v3 attribute network model uses the ImageNet pre-trained model as the initialization model and gradient descent algorithm (SGD) is used for weight learning.

C. Causal Learning Of Connections Between Garbage Attributes And Operation Mode Decision

The causal learning technology is introduced to find out which attributes affect the cleaning operation modes. These attributes will be used to guide the construction of subsequent fuzzy inference networks. In this paper, a directed acyclic graph (DAG) is used to represent the variable relationship between the cause and effect graphs, where the node connections between the cause and effect graphs are represented by directed arrows. The variable that the directed arrow points to represents the "parent node", and the variable facing away from the directed arrow represents the "child node". The set of nodes is denoted by $\vec{X} = (X_1, X_2, \ldots, X_P)$. If the parent node of one node is given in DAG, then all non-child nodes of this node are independent. According to the full probability formula and conditional independence, the joint distribution of variables of the DAG can be decomposed as follows:

$$P(x_1, \ldots, x_n) = \prod_{i=1}^{p} P(x_i \mid pa_i) \quad (4)$$

where pa_i represents the set of "parent nodes" pointed to X_i. By coding the prior knowledge, we can get a local causality diagram composed of nodes and edges. If node A points to B, then A is the parent of B. We can say that the variable A is the direct cause of B. The attributes of garbage is denoted as intervention variable V, where $V_i \subseteq \{0,1\}$. The remaining attributes are denoted as X_i, where $X_i \subseteq \{1,2,3\}$. Unobservable variables are expressed as U, and decision mode variables are denoted as Y_j, where $Y_j \subseteq \{0,1\}$. The corresponding cause-effect diagram is shown in Fig. 4.

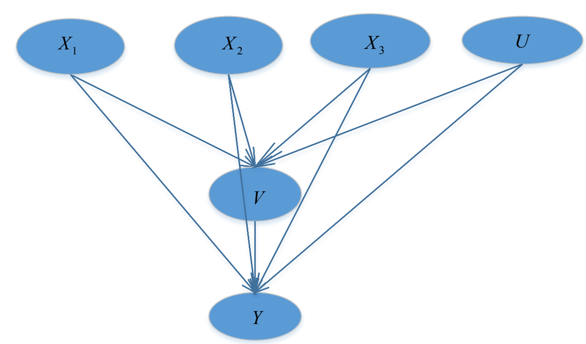


Figure 4. Causality diagram

The joint distribution of DAG variables can be decomposed as follows:

$$\begin{aligned} &P(X_1, X_2, X_3, U, V, Y) \\ &= P(X_1)P(X_2)P(X_3)P(U) \\ &\cdot P(V \mid X_1, X_2, X_3, U) \\ &\cdot P(Y \mid X_1, X_2, X_3, V, U) \end{aligned} \quad (5)$$

The DAG is also a data generation model, which is equivalent to the following non-parametric structure model:

$$X_i = f_i(pa_i, \propto_i), i = 1, \ldots, p \quad (6)$$

In order to predict the connection between the input and output of the observation data, we need to intervene, by changing the current value of the input. The introduced "intervention operator" is expressed as $do(X_i) = x_i'$ in DAG. Meanwhile, all the directed edges pointing to X_i in the DAG are removed and the value of X_i is set to a fixed constant when making causal estimates. As a result, a new causal expansion graph can be obtained and its joint distribution can be written as

$$P(x_i, \ldots, x_n \mid do(X_i) = x_i') = \frac{P(x_i, \ldots, x_n)}{P(x_i \mid pa_i)} I(x_i = x_i') \quad (7)$$

According to the "do" operator, the average causal effect of the binary variable A on B is defined as

$$ACE(V \to Y) = E\{Y \mid do(V) = 1\} - E\{Y \mid do(V) = 0\} \quad (8)$$

When the causality diagram and "do" operator are known, the causal effect between the attributes of the garbage and the operation mode can be estimated. Using the "Dowhy" causal reasoning toolbox provided by Microsoft for causal analysis, the results between the garbage attributes and the operation mode decision are shown in the table below.

TABLE I. IMPACT OF CAUSAL LEARNING ON THE OPERATING MODE

Attributes	State	Shape	Size	Distribution	Operation mode
Impact factor	**0.3250**	**0.1412**	**0.2806**	0.0093	Adsorption
	0.9882	-0.0001	-0.0052	0.0001	Erasing
	-0.1062	0.0798	**0.2833**	**0.3802**	Grasping
	-0.1569	0.0442	**0.1141**	**-0.5179**	Sweeping

In Table I, the sign of impact factors indicates the direction of cause and effect. The positive value indicates the intervention is the cause, and the negative value indicates the intervention variable is the effect. The greater the absolute value is, the closer the causal relationship is. Conversely, the connection is weaker. If we ignore the case that the absolute value of the influence factor is lower than 0.1, it is easy to find out the relationships between attributes of garbage and operation modes. The attributes that affect the selection of adsorption mode are state, size and shape. For erasing mode, the decisive attribute is state. The main attributes that determines the choice of grasping include distribution, size, and state. The attributes that significantly affect the sweeping mode are state, size, and distribution. The above results have a great role in refining the decision rules, which is used to design the subsequent fuzzy inference neural network.

IV. Fuzzy Inference Network For Operation Mode Decision

In this paper, adaptive fuzzy inference neural network is used to realize the inference decision from garbage attribute to operation mode. The adaptive fuzzy inference system ANFIS [31] is a combination of a fuzzy inference system (FIS) and adaptive network. According to the results of causal learning (Table I), we redefine the rule layer, in which the number of rules is defined as six, corresponding to six rules respectively. The rules are expressed as follows:

(1) Adsorption mode: Solid, flat objects.

(2) Erasing mode: Liquid objects.

(3) Grasping mode: Overall large objects.

(4) Sweeping mode: Scattered, solid, non-flat objects.

(5) Grasping mode: Overall and medium size objects.

(6) Sweeping mode: Solid, whole, scattered, non-flat objects.

The coding of the above rules can be expressed in matrix W_1 and W_2, where W_1 and W_2 is a 9 * 6 and 6 * 4 sparse matrix respectively. The matrix W_1 represents the weight connection relationship between the fuzzy layer and the rule layer, and the matrix W_2 represents the weight connection relationship between the rule layer and the decision output layer. The structure of the final ANFIS fuzzy neural network for the decision of the operation mode is shown in Fig.5.

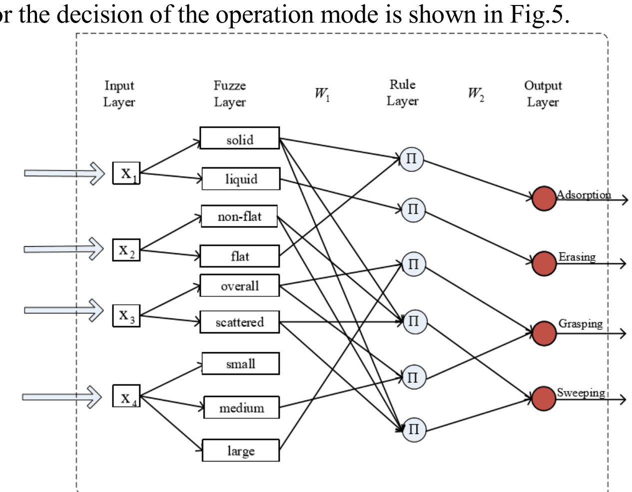


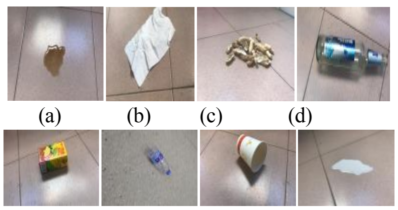
Figure 5. Adaptive fuzzy inference network for operation mode decision

V. Experimental Results And Analysis

A. Experimental Data Set

There are many kinds of garbage in home environment, with big differences in color, shape and size. How to choose the attribute reasonably is the precondition of robot intelligent cleaning. For simplicity, only four attributes of state, shape, size and distribution are considered in this paper. In the experiment, we chose 25 kinds of garbage which are common in our life as the experimental objects. Since there is no related public data set, the data used in the experiment is collected by ourselves in the actual home environment. There are 1513 images in the dataset, and each image usually contains only one kind of garbage. Among them, there are

911 pictures taken at a fixed distance of 0.5 meters and 602 pictures taken at a non-fixed distance. In order to increase the sample size of network training, the image data enhancement tool Image Data Generator provided by Keras is used in the experiment to perform horizontal mirror flip, random rotation, cropping, scaling and other processing on the training samples. Finally, the total number of sample images is expanded to 6052, of which 3644 pictures are generated with fixed distance. When training networks models, 60% of the total samples are used as training samples, 20% of the total samples are used as test samples, and the remainder samples are used as validation samples. It is noted that the total samples selected for size attribute network model training and testing come from 3644 pictures generated with fixed distance. Some examples of garbage samples are shown in Fig. 6.



(a) (b) (c) (d)

(e) (f) (g) (h)

Figure 6. Examples of garbage samples

B. Attribute Learning

We compared different attribute learning schemes, including attribute learning in single task mode, attribute learning in multi-task attribute learning without grouping, and grouped multi-task attribute learning considering heterogeneity. The results are listed in Table II.

Single task mode attribute learning, that is, each attribute is learned by a special model. The complete model is composed of 4 Inception networks. The accuracy of state, shape, distribution and size of the single task learning method is 99.38%, 84.62%, 66.31%, 98.21% respectively. The results show that the single-task attribute learning model is effective for learning state, distribution, and size attributes. However, it is not suitable for distribution attribute training, and it is difficult to accurately distinguish the overall and the scattered objects. Fig. 3 shows the multi-task attribute learning model with grouping. An inception network is used to train multiple attributes at the same time in the way of multi-task joint learning. Firstly, all samples are used to train the state, shape, and distribution attributes. Then we will train the weight parameters of the size attribute subnetwork. The initial learning rate is set to 0.005. After that, the samples taken at a fixed distance are used to train the size attributes. Meanwhile, the obtained previously weight parameters of the network connection are fixed, and the learning rate is set to 0.0025. Finally, the accuracy of state, shape, distribution and size of the multi task learning method without grouping is 99.54%, 97.78%, 98.92% and 94.92% respectively. And the accuracy of multi task learning method with grouping reaches 99.74%, 97.93%, 99.90% and 99.38% for state, shape, size and distribution attribute. Compared with without grouping attribute learning schemes, the accuracy of the grouped multi-task joint learning has significantly improved because it considers both the correlation of the attributes and the heterogeneity of the attributes.

TABLE II. RESULTS OF DIFFERENT ATTRIBUTE LEARNING (%)

Attribute / Methods	state	shape	distribution	size
Single task mode	99.38	84.62	66.31	98.21
multi-task without grouping	99.54	97.78	98.92	94.92
multi-task with grouping	99.74	97.93	99.90	99.38

C. Method Comparison

In this section, the proposed method in this paper is compared with other methods. The first method to be compared is the method which directly uses the Inception-V3 deep network for operation mode decision without attribute learning. It directly completes the mapping from the image to the decision space through learning. The result shows that the test accuracy of this method is 92.32%.

In addition, considering that decision trees, SVMs, and fuzzy neural networks are common inference methods, the performance of these methods combined with attribute learning is tested and compared. Finally, the improved fuzzy inference network method combined with causal inference and attribute learning proposed in this paper is tested. The final test results of various methods are listed in Table IV. The results show that the decision accuracy of the decision tree is 97.23% and the accuracy of the SVM decision is 97.68%. Note that the performance of fuzzy neural networks is related to the number of hidden rule layer neurons. Thus we test the results of fuzzy neural networks with different number of rules (Table III).

TABLE III. ANFIS TEST RESULTS WITH DIFFERENT RULE LAYERS NEURONS LEARNING (%)

Epoch (1000) / Rules	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Loss	Time (s)
2	7.59	22.60	45.87	63.53	74.42	97.52	97.52	97.52	94.38	94.38	94.38	94.38	94.38	94.38	0.05	92
4	29.20	26.07	26.07	46.36	48.67	48.34	74.58	74.58	74.58	74.58	87.62	87.62	97.02	97.02	0.18	88
6	61.38	64.52	94.88	94.88	94.88	94.88	94.88	94.88	94.88	94.88	94.88	94.88	94.88	94.88	0.03	80
8	91.08	93.39	.93.89	93.89	97.02	97.02	98.01	98.01	98.01	98.01	98.01	98.01	98.01	98.01	0.02	96
10	48.34	63.69	93.06	98.01	83.49	98.01	98.01	98.01	98.01	98.01	98.01	98.01	98.01	98.01	0.04	92
12	94.88	94.88	98.01	98.01	98.01	98.01	98.01	98.01	98.01	98.01	98.01	98.01	98.01	98.01	0.01	50
14	95.70	98.01	98.01	98.01	98.01	98.01	98.01	98.01	98.01	98.01	98.01	98.01	98.01	98.01	0.04	99
16	41.58	62.54	88.61	93.23	98.01	98.01	98.01	98.01	98.01	98.01	98.01	98.01	98.01	98.01	0.02	119
18	48.34	62.87	64.68	79.86	93.89	94.88	98.01	98.01	98.01	98.01	98.01	98.01	98.01	98.01	0.02	103
20	79.37	79.37	79.37	79.37	79.37	98.01	98.01	98.01	98.01	98.01	98.01	98.01	98.01	98.01	0.01	144
22	2.31	43.56	61.22	61.22	61.22	61.22	61.22	90.42	92.73	97.52	97.52	97.52	.97.52	97.52	0.02	152
24	16.83	61.22	61.22	85.80	86.79	86.79	86.79	86.79	86.79	86.79	86.30	86.30	84.98	49.87	0.03	160

It can be found from the above table that when the number of rules is 8-20, the network can get the best result 98.01% in 10000 iterations. In particular, when the number of rules is 10-14, the network performance is optimal. Considering stability, accuracy and convergence rate, the number of rules of adaptive fuzzy neural network is set to 12 in the experiment, and the total number of network parameters to be learned is 96. It is noted that there is still redundancy in the number of rules. In contrast, there are only six rules in the rule layer of ANFIS fuzzy reasoning network based on the causal analysis proposed in this paper, and only 37 parameters need to be trained. Moreover, the system is stable after 6000 iterations, and the accuracy can reach the best value 98.01% at present.

TABLE IV. RESULTS OF THE ACCURACY OF VARIOUS METHODS

Methods	Accuracy（%）
Direct mode decision based on deep learning	92.32
Attribute Learning + Decision Tree	97.23
Attribute Learning + Fuzzy Neural Network	98.01
Attribute Learning + SVM	97.68
Attribute learning + causal reasoning + improved ANFIS network	98.01

VI. CONCLUSION

According to the characteristics of garbage, this paper proposes a cleaning robot operation mode decision model based on attribute learning and related attribute causal reasoning. The decision-making process is divided into two stages. In the first stage, the powerful feature representation ability of neural network is used to imitate the way of human analysis and dispose garbage according to the "attribute" feature. In the second stage, the reasoning network simplifies the structure design with the help of causal analysis. The parameters to be learned in the model are reduced by nearly two-thirds compared with the conventional fuzzy neural network, and it has good interpretability. The above scheme effectively avoids the semantic gap problem in the direct reasoning scheme.

Although the proposed method has achieved good results, there is still room for improvement. At present, we quantify the size attributes in our method, but in fact, it is more appropriate to describe the size attributes with continuous values. In order to get better training effect, it is considered to relabel the size attributes and set a separate loss function. In addition, the connection between attributes and cleaning operation modes can also be used to guide the design of attribute learning network. These issues will be further improved in our future work.

In addition, due to the complexity of the definition of garbage, whether the object is garbage is actually affected by the subjective value of human beings. The useful things falling on the ground may not be treated as garbage. In addition, the size of the robot itself and the size of the operation mechanism should be considered comprehensively to make decision. To simplify the problem in this paper, we only select limited types of garbage and make operation decisions from the perspective of cleaners according to the requirements of ordinary sweeping robots in daily home environment.

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