Fuzzy Logic Model of Surprise

Rui Qiao[a,b], Yajun Feng[c], Xiaolei Zhong[d], Qiaojia Liu[e], Heng He[a,b]
[a] College of Computer Science and Technology, Wuhan University of Science and Technology, Wuhan, China
Email: qiaorui@wust.edu.cn
[b] Intelligent Information Processing and Real-time Industrial System Hubei Province Key Laboratory, Wuhan, China
[c] Air Force Early Warning Academy, Wuhan, China
Email: fyj809@sohu.com
[d] School of Software, Huazhong University of Science, Wuhan, China
Email: zhong@jfj-edu.com
[e] Tianjin Modern Vocational Technology College, Tianjin, China
Email: freeqr@163.com

***Abstract*— Emotional agents are useful to variety of computer applications. This paper focuses on the emotion of surprise. Surprise can be considered as the automatic reaction to a mismatch, which plays an important role in the behaviors of intelligent agents. We represent psychological theories of surprise through fuzzy inference systems, as fuzzy logic helps to capture the fuzzy and complex nature of emotions. We infer the degree of surprise from four factors relating to it by three kinds of fuzzy inference systems respectively, and propose fuzzy inference rules as well as reasoning parameters for the systems. Case study shows the surprise generation process by fuzzy inference system. The surprise inference system can be applied into the decision making process of agents in uncertain environments.**

***Index Terms*— surprise, fuzzy inference, emotion simulation, agent**

I. Introduction

Emotional agents are useful to variety of computer applications, which are modeled and developed by many researchers recently. This paper focuses on the emotion surprise. Surprise is the automatic reaction to a mismatch. It is a felt reaction/response of alert and arousal due to an inconsistency (discrepancy, mismatch, non-assimilation, lack of integration) between an incoming input and our previous knowledge, in particular an actual prediction or a potential prediction [1].

According to [2], [3], surprise plays an important role in the cognitive activities of intelligent agents, especially in attention focusing [4]–[7], learning [8] and creativity [9], [10]. Articles [2], [3], [5] holds that surprise has two main functions, the one informational and the other motivational: it informs the individual about the occurrence of a schema-discrepancy, and it provides an initial impetus for the exploration of the unexpected event. Thereby, surprise promotes both immediate adaptive actions to the unexpected event and the prediction, control and effective dealings with future occurrences of the event. Experiencing surprise has also some effects on humans other behaviors, for example, expression through facial expressions [11].

Article [12] summarized the main factors affecting surprise intensity. A number of experiments in [13] show that expectancy disconfirmation is indeed an important factor for surprise. The experimental results shown in [14] shows in a number of experiments unexpected events that are seen as more important by a subject are experienced as more surprising. Article [15] shows that an unexpected event is seen as less surprising if the surprised person is offered a reasonable explanation that more or less justify the occurrence of the surprising event. Several experiments [16] show that amongest other factors, events that are familiar are less surprising.

Papers [2], [17]–[19] proposed a surprise-based agent architecture and showed some experiments results. The author computed the intensity of surprise by the degree of unexpectedness of events.

Fuzzy logic has various applications, such as [20]–[29]. Since fuzzy logic helps to capture the fuzzy and complex nature of emotions, a lot of research work uses fuzzy rules to explore the capability of fuzzy logic in modeling emotions [3], [30]–[35] and recognizing emotions [36]–[38].

Following the above-mentioned work to extrapolate psychologically grounded models of emotion through fuzzy logic systems, we represent psychology theories of surprise through fuzzy logic systems, which are implemented using Matlab. The rest of the paper is organized as follows: Section2 gives a brief introduction for fuzzy sets and inference. Section3 presents the mamdani fuzzy inference system. Section4 and Section5 present the Sugeno fuzzy inference system. Section6 takes a case study. Section7 makes a comparison.

II. Fuzzy Sets and Fuzzy Inference

A fuzzy set [39] is a pair (U, μ) where U is a crisp set and μ is a function denoted by $\mu : U \to [0, 1]$. For each

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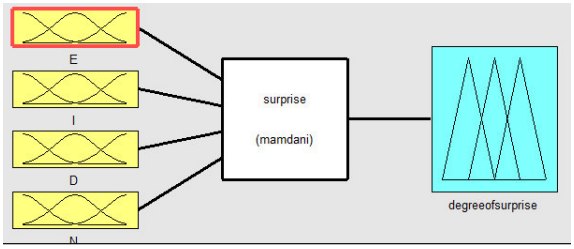

Figure 1. Mamdani inference system

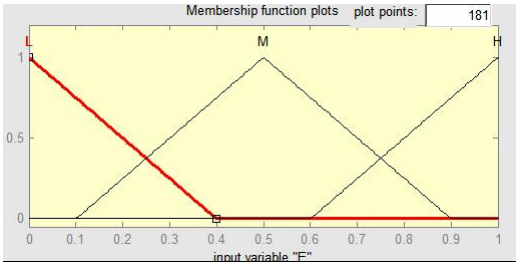

Figure 2. Membership functions for input variables in mamdani

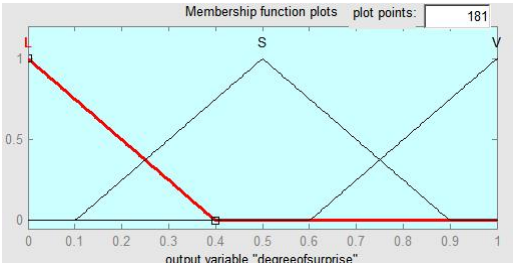

Figure 3. Membership functions for output variables in mamdani

$x \in U$, the value $\mu(x)$ is called the grade of membership of x in (U, μ).

For a finite set $U = \{x_1, ...x_n\}$, the fuzzy set (U, μ) is often denoted by $\{\mu(x_1)/x_1, ..., \mu(x_n)/x_n\}$. Let $x \in U$, then x is called not included in the fuzzy set (U, μ) if $\mu(x) = 0$, x is called fully included if $\mu(x) = 1$, and x is called a fuzzy member if $0 < \mu(x) < 1$. The function μ is called the membership function of the fuzzy set (U, μ).

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic [40]. In detail, fuzzy inference is a method that interprets the values in the input vector, and based on some set of rules, assigns values to the output vector [40], [41]. Fuzzy inference system(FIS) as major unit of a fuzzy logic system uses IF-THEN rules, given by, IF antecedent, THEN consequent [41]. The FIS formulates suitable rules, and based upon the rules the decision is made.

We adopt Mamdani and and Sugeno fuzzy inference methods [40], [41] for our systems in succession, and make a comparison between them.

Our fuzzy inference system applies Matlab to implement reasoning process. Matlab is an advanced interactive software package specially designed for scientific and engineering computation, which has been proven to be a very flexible and usable tool for solving problems in many areas. There exist large set of toolboxes including Fuzzy logic toolbox, or collections of functions and procedures, available as part of the Matlab package [41].

III. Mamdani

A. Fuzzy Inference System

Mamdani is the most commonly seen fuzzy methodology, whose rules' form is more intuitive than Sugeno fuzzy inference method. The Mamdani fuzzy inference system is shown in Fig. 1. It has four inputs, one output, and eighty-one rules.

In our work, the four factors, i.e. expectation disconfirmation(E), importance of observed event(I), difficulty of explaining/fitting it in schema(D), novelty(N) of surprise emotion are all divided into three levels. We design three fuzzy sets i.e. high(H), middle(M) and low(L) for the levels. The intensity of surprise is divided into three levels. We design three fuzzy sets: very surprise(V), surprise(S) and little surprise(L) for the levels.

We take the four factors as inputs of the inference system, and the intensity of surprise as output. The membership functions for both inputs and output adopt the "trimf" function, which are shown in Fig. 2 and Fig. 3 respectively.

Fuzzy rules are IF-THEN rules to capture the relationship between inputs and outputs. According to the psychology theories [13]–[16], we propose fuzzy rules of the emotion surprise. There are eighty-one fuzzy rules for the fuzzy system. In order to save space, only fourteen of them are listed in Table 4. The form of rules is shown in Fig. 4.

In Table I and Fig. 4, E,I,D,N represent expectation

TABLE I.
Mamdani fuzzy rules for surprise

E	I	D	N	intensity of surprise
H	H	H	H	V
H	H	H	M	V
H	H	H	L	V
H	M	M	M	S
H	M	M	L	S
H	M	L	H	S
H	M	L	M	S
H	M	L	L	S
L	H	L	L	L
L	M	H	H	S
L	M	H	M	S
L	L	L	H	L
L	L	L	M	L
L	L	L	L	L

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1. If (E is H) and (I is H) and (D is H) and (M is H) then (degreeofsurprise is V) (1)
2. If (E is H) and (I is H) and (D is H) and (M is M) then (degreeofsurprise is V) (1)
3. If (E is H) and (I is H) and (D is H) and (M is L) then (degreeofsurprise is V) (1)
4. If (E is H) and (I is H) and (D is M) and (M is H) then (degreeofsurprise is V) (1)
5. If (E is H) and (I is H) and (D is M) and (M is M) then (degreeofsurprise is V) (1)
6. If (E is H) and (I is H) and (D is M) and (M is L) then (degreeofsurprise is S) (1)
7. If (E is H) and (I is H) and (D is L) and (M is H) then (degreeofsurprise is V) (1)
8. If (E is H) and (I is H) and (D is L) and (M is M) then (degreeofsurprise is S) (1)
9. If (E is H) and (I is H) and (D is L) and (M is L) then (degreeofsurprise is S) (1)
10. If (E is H) and (I is M) and (D is H) and (M is H) then (degreeofsurprise is V) (1)
11. If (E is H) and (I is M) and (D is H) and (M is M) then (degreeofsurprise is V) (1)

Figure 4. Mamdani fuzzy rules for surprise

disconfirmation, importance of observed event, difficulty of explaining, and novelty respectively. H,M,L denote high, middle, and low degrees, while V,S,L denote very surprise, surprise, and little surprise respectively. Each rule occupies a row. For example, the first row in the table means: For an agent, if expectation disconfirmation, importance of observed event, difficulty of explaining, and novelty respectively are all high, then the agent is very surprise.

B. Fuzzy Reasoning

The steps of fuzzy reasoning in Mamdani performed by FISs in Fuzzy logic toolbox [21,27] are: 1 Fuzzification; 2 Combine inputs(applying fuzzy operator); 3 Implication; 4 Combine outputs(aggregation); 5 Defuzzification.

Step1: Fuzzification. The first step is to take the crisp inputs and determine the degree to which they belong to each of the appropriate fuzzy sets via membership functions. The input is always a crisp numerical value limited to the universe of discourse of the input variable, and the output is a fuzzy degree of membership in the qualifying linguistic set. Designed uncertainty enables us to carry on the computation in those areas that are not clearly defined by crisp values.

Step2: Combine inputs(applying fuzzy operator). If the antecedent of a given rule has more than one part, the fuzzy operator is applied to obtain one number that represents the result of the antecedent for that rule. The input to the fuzzy operator is two or more membership values from fuzzified input variables. The output is a single truth value. We choose method ”min” for AND operator among the methods ”min” and ”prod”. There are only AND operators and do not exist OR operators in our fuzzy rules.

Step3: Implication. Implication is used to obtain the membership function degree from antecedent of a rule to consequent of a rule. A consequent is a fuzzy set represented by a membership function, which weights appropriately the linguistic characteristics that are attributed to it. The consequent is reshaped using a function associated with the antecedent a single number. The input for the implication process is a single number given by the antecedent, and the output is a fuzzy set. Implication is implemented for each rule. We choose method ”prod” for implication process among the methods ”min” and ”prod”.

Step4: Combine outputs(aggregation). Aggregation is the process by which the fuzzy sets that represent the outputs of each rule are combined into a single fuzzy set. The input of the aggregation process is the list of truncated output functions returned by the implication process for each rule. The output of the aggregation process is one fuzzy set for each output variable. We adopt method ”sum” for aggregation process among the methods ”max”, ”probor” and ”sum”.

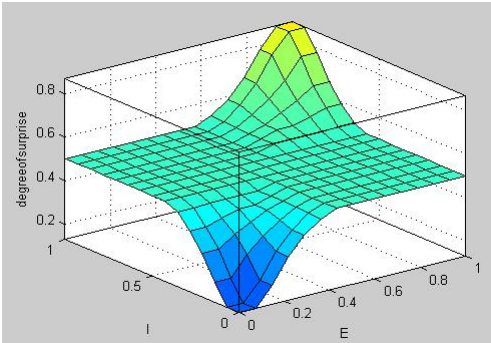

Figure 5. I E surface for mamdani

Step5: Defuzzification. When the FIS is used as a controller, it is necessary to have a crisp output. Therefore in this case defuzzification method is adopted to best extract a crisp value that best represents a fuzzy set [21]. As much as fuzziness helps the rule evaluation during the intermediate steps, the final desired output for each variable is generally a single number. The input for the defuzzification process is the aggregate output fuzzy set, and the output is a single number. Defuzzification methods include ”max-membership” method, ”centroid” method, ”weighted average” method, ”mean-max membership” method. We adopts the ”centroid” method, which is the most efficient and used defuzzification method. The method determines the center of the area of the combined membership functions.

There are six surfaces in three dimensions space. The values of two chosen inputs are both fixed as 0.5, altering the other two inputs: N-D,I-N,I-E,I-D,E-N and E-D respectively. Intensity of surprise is the output. Take I-E surface as a representation shown in Fig. 5.

The Matlab code constructing the Mamdani fuzzy inference system is shown in [42].

IV. Sugeno

A. Fuzzy Inference System

The Sugeno fuzzy inference system is shown in Fig. 6. Like Mamdani system, it has four inputs, one output, and eighty-one rules.

The inputs with membership functions are the same as Mamdani, which are shown in Fig. 2. Our rules in Sugeno model has the same consequent ”the-1th” in all inputs cases, which represents ”$1/4(E + I + D + N)$”. There are eighty-one fuzzy rules for the fuzzy system, part of which are listed in Fig. 7.

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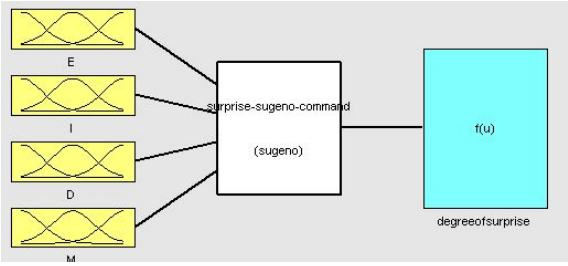

Figure 6. Sugeno inference system

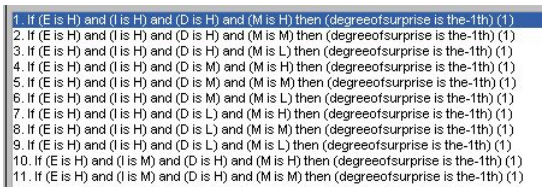

Figure 7. Sugeno inference rules

B. Fuzzy Reasoning

Step1 and Step2 for reasoning are the same as Mamdani. The rest steps are as follows:

Step3: Implication is used to obtain the single number from antecedents of a rule to consequents of a rule. The input for the implication process is a single number, and the output is a single number computed by the linear function. Implication is implemented for each rule.

Step4: The output level z_i of each rule is weighted by the firing strength $w_i = AndMethod(F1(E), F2(I), F3(D), F4(N))$ of the rule. $F1(E), F2(I), F3(D), F4(N)$ are membership functions for inputs E, I, D, N respectively. The final output of the system is the weighted average of all rule outputs [41], computed as

$$finaloutput = \frac{\sum_{i=1}^{N} w_i z_i}{\sum_{i=1}^{N} w_i} \quad (1)$$

.

There are six surfaces in three dimensions space like Mamdani system. Take I-E surface as a representation shown in Fig. 8.

Part of the Matlab code constructing the Sugeno fuzzy inference system is shown in Appendix A. The

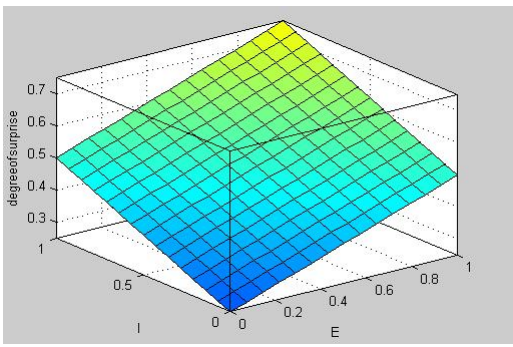

Figure 8. I E surface for sugeno

Figure 9. Training data

remaining code is similar to Mamdani except that the output membership function number in ruleList is 1.

V. Sugeno from Anfis

In the former two inference systems, we choose the membership functions and rules according to the features of inputs and outputs. Anfis [43] is neural adaptive learning technology. This technology provides a method for the fuzzy modeling process to study a dataset. The parameters of input and output membership functions in Sugeno inference system are trained to adapt the input/output data in Appendix B. We create and train Sugeno-type fuzzy systems using the Anfis Editor GUI [40]. The steps are as follows:

1) Load the data. We load a training data set "surprise.dat" in Appendix A.3 that contains the desired input/output data of the system to be modeled. The training data are annotated in blue as circles, shown in Fig. 9.

2) Generate or load the FIS model structure. We generate the initial FIS model by grid partitioning on the data "surprise.dat".

3) Train the FIS using optimization methods. After loading the training data and generating the initial FIS structure, we start training the FIS. We choose "hybrid" as the optimization method. The optimization methods train the membership function parameters to emulate the training data. The maximum number of training Epochs is setted as "40". and the training Error Tolerance is setted as "0" . The training process stops whenever the maximum epoch number is reached or the training error goal is achieved.

The training action adjusts the membership function parameters and displays the error plots in Fig. 10. The training data and FIS output are annotated in blue as circles and in red as solid points respectively shown in Fig. 11.

In the Sugeno system, the type of the membership functions of input is fixed as "trimf" in both the initial and the trained systems, while the parameters of the membership functions changes from [0 1 2], [0.995 1.99 2.99], [2 3 4] before training to [0 1 1.993], [1.003 2 2.996], [2.005 3 4] after training. The parameters of membership functions of output is zero before training. After training,

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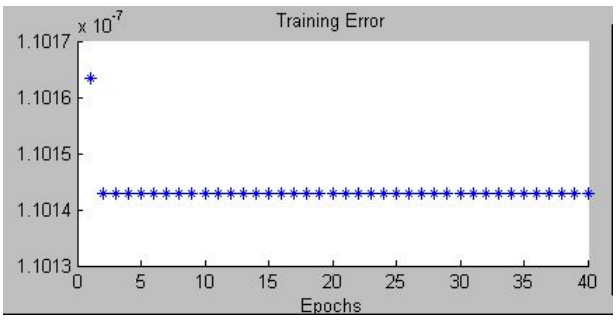

Figure 10. Training error

Figure 11. Training data vs FIS output

the parameters changes into non-zero values.

The Sugeno fuzzy inference system training from Anfis is shown in Fig. 12. It has also four inputs, one output, and eighty-one rules.

The membership functions of inputs in this system shown in Fig. 13 have different parameters from the two systems Mamdani and Sugeno introduced in the previous sections. There are eighty-one linear functions for the output "degreeofsurprise". Part of eighty-one fuzzy rules for the system are listed in Fig. 14. Take "I-E" surface among the six surfaces as a representation shown in Fig. 15.

VI. Case Study

The following scenes can occur in a game or combat simulation, where agents make decisions strengthened by

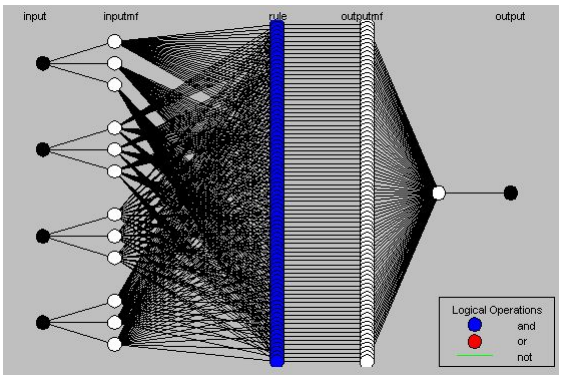

Figure 12. Sugeno system from Anfis

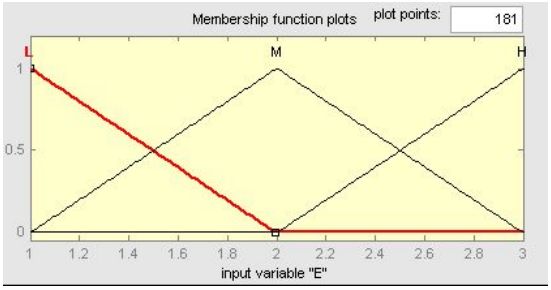

Figure 13. Fuzzy sets for factors of surprise after train

1. If (E is L) and (I is L) and (D is L) and (N is L) then (degreeofsurprise is out1mf1) (1)
2. If (E is L) and (I is L) and (D is L) and (N is M) then (degreeofsurprise is out1mf2) (1)
3. If (E is L) and (I is L) and (D is L) and (N is H) then (degreeofsurprise is out1mf3) (1)
4. If (E is L) and (I is L) and (D is M) and (N is L) then (degreeofsurprise is out1mf4) (1)
5. If (E is L) and (I is L) and (D is M) and (N is M) then (degreeofsurprise is out1mf5) (1)
6. If (E is L) and (I is L) and (D is M) and (N is H) then (degreeofsurprise is out1mf6) (1)
7. If (E is L) and (I is L) and (D is H) and (N is L) then (degreeofsurprise is out1mf7) (1)
8. If (E is L) and (I is L) and (D is H) and (N is M) then (degreeofsurprise is out1mf8) (1)
9. If (E is L) and (I is L) and (D is H) and (N is H) then (degreeofsurprise is out1mf9) (1)
10. If (E is L) and (I is M) and (D is L) and (N is L) then (degreeofsurprise is out1mf10) (1)
11. If (E is L) and (I is M) and (D is L) and (N is M) then (degreeofsurprise is out1mf11) (1)

Figure 14. Fuzzy rules for sugeno system from anfis

emotions. We both implement the fuzzy inference process and produce an interface through Matlab. The function in Matlab fuzzy logic toolbox calculating output from inputs is shown in Appendix C.

A. Scene 1

Here is a scene. An agent gets lost in mountains. It is at the foot of a mountain, hungry and thirsty. It decides to climb over the mountain to search food and water on the other side of the mountain. When it climbs over the mountain, it finds some objects on the other side. The objects represent different degrees of stimulating factors sequence, which next stimulate different intensities of surprise. Table II shows the crisp inputs and outputs of three kinds of fuzzy inference systems in the situations. "E","I","D","N" represent inputs, while "mamdani","sugeno","anfis" represent outputs of mamdani, sugeno, sugeno from anfis systems respectively.

In the Mamdani system, the output value can be attributed to one fuzzy set with the max membership value among three fuzzy sets "little surprise", "surprise", "very surprise". Appendix C.1.1 includes the Matlab program to

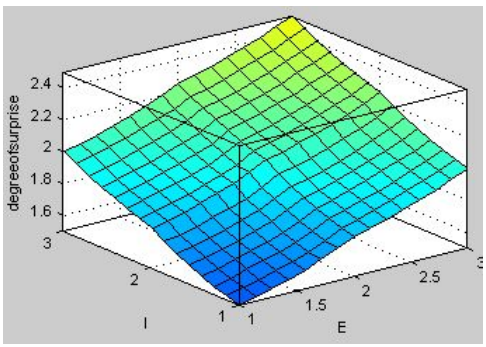

Figure 15. I E surface for sugeno from anfis

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TABLE II.
"THE OTHER SIDE OF THE MOUNTAIN"

Object	E	I	D	N	mamdani	sugeno	anfis
Monster	0.9	0.8	0.9	0.9	0.8700	0.8750	0.9000
Farmland	0.1	0.9	0.1	0.1	0.1300	0.3000	0.4400
Orchards	0.1	0.9	0.1	0.1	0.1300	0.3000	0.4400
River	0.1	0.9	0.1	0.1	0.1300	0.3000	0.4400
Lake	0.1	0.9	0.1	0.1	0.1300	0.3000	0.4400
Sea	0.9	0.9	0.5	0.1	0.5000	0.6000	0.6800
Mountain	0.1	0.8	0.1	0.1	0.1300	0.2750	0.4200
Buildings	0.5	0.8	0.1	0.1	0.4245	0.3750	0.5000

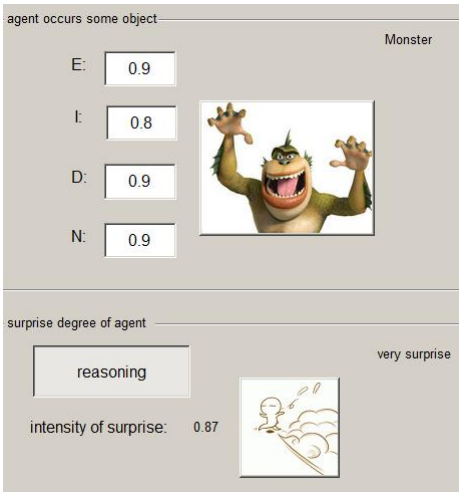

Figure 16. Scene 1

compute the membership values of the three fuzzy sets. In Sugeno from Section4 and Sugeno from Section5, in order to attribute the output value into one fuzzy set, its necessary to add border values.

The varying intensities of surprise result in different behaviors. In this case, the relationship between the surprise degrees and behaviors can be described by If-else rules: If agent is very surprise, then actions are cry and run away; If agent is surprise, then action is cry; If agent is little surprise, then there's only facial expression.

The interface for scene 1 includes upper and lower parts. In the upper part, there is a button. Click the button to randomly generate a picture of one object among the eight objects in Table II. In the lower part there is another button. To click on this button will call matlab reasoning process that generates the picture of the degree of surprise among three degrees. The reasoning process adopts Mamdani inference system. Fig. 16 shows one screenshot of the application for scene 1.

B. Scene 2

Here is a scene revised from [44] and [18]. An agent is in an environment with four possible objects: a house, a church, a shop, a new building. The agent can receive the building while it can not know the function of the building at the beginning. When it knows the function of the building, it will be surprise with different intensities. The objects in Table III represent different degrees of stimulating factors sequence, which next stimulate different intensities of surprise as case1. Table III shows the crisp inputs and output of three kinds of inference systems in the situations.

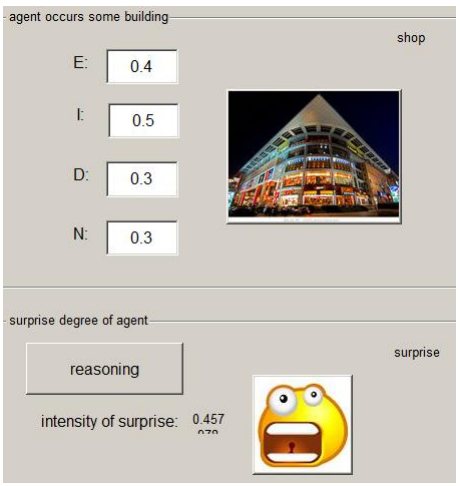

Figure 17. Scene 2

TABLE III.
BUILDINGS

Object	E	I	D	N	mamdani	sugeno	anfis
House	0.33	0.5	0	0	0.1300	0.2075	2.0000
Church	0.7	0.5	0.8	0.4	0.5420	0.6000	0.6800
Hotel	0.55	0.5	0.7	0.4	0.5000	0.5375	0.6300
Shop	0.4	0.5	0.3	0.3	0.4580	0.3750	0.5000
New	1	0.5	0.9	0.9	0.8700	0.8250	0.8600

The Matlab program to compute the membership values of the three fuzzy sets is the same as case1, so it's omitted in Appendix.

The interface for scene 2 is similar to scene 1, except that in the upper part, the pictures generates randomly from five buildings. The reasoning process also adopts Mamdani inference system. Fig. 17 shows one screenshot of the application for scene 2.

VII. COMPARISON

In order to compare, we call Mamdani inference system in section3 as Mamdani, Sugeno system in section4 as Sugeno1, Sugeno system in section5 as Sugeno2.

A. Inputs Variables

All of the three kinds of inference systems have the same type "trimf" for membership functions of inputs variables. Inputs variables of Mamdani and Sugeno1 have the same membership functions parameters [-0.4 0 0.4],[0.1 0.5 0.9],[0.6 1 1.4]. while Sugeno2 has different

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membership functions parameters [0 1 1.993],[1.003 2 2.996],[2.005 3 4].

B. Rules

In Mamdani, the consequents of rules are fuzzy sets. In Sugeno1 and Sugeno2, the consequents of rules are linear functions. All rules in Sugeno1 have the same linear function as consequents. Unlike Sugeno1, consequents of rules in Sugeno2 are 81 different linear functions.

C. Outputs Variables

The output variables of Mamdani are fuzzy sets. The output variable of Sugeno is one linear function, while output variable of anfis are 81 linear functions.

D. Input-output Surfaces

The surface is a plain one in Sugeno1. Comparatively in Sugeno2, the output values from inputs in different scopes are more clearly distinguished in Sugeno2.

E. Case Study

In Mamdani, the output value can be attributed to to one fuzzy set with the max membership value among three fuzzy sets ”little surprise”, ”surprise”, ”very surprise”. The different fuzzy sets correspond to different actions. In Sugeno1 and Sugeno2, in order to attribute the output value into one fuzzy set, its necessary to add border values. However, the selection of border values has no principles to follow.

VIII. Conclusions

We have represent psychology theories of emotion surprise through three fuzzy inference systems and have made case study. The method can be used to other emotions. This work takes the common membership function trimf for inputs and output for Mamdani. However, the membership function more in line with the actual situation should take shape in the actual application. Fuzzy rules and the membership functions of mamdani can be generated by the method proposed in papers [45] as a future work. The surprise inference system will be applied into the decision making process of agents in uncertain environments.

Appendix

A Sugeno fuzzy inference system

```
a=addvar(a,'output','degreeofsurprise',
[0 15]);
 a=addmf(a,'output',1,'1','linear',
 [1 1 1 1 0]);
writefis
(a,'surprise-sugeno-command.fis');
```

B Anfis training data

In every five numbers, the former four numbers represent inputs of FIS system, the fifth number is the desired output.

```
3 3 3 3 3    3 3 3 2 2.75  3 3 3 1 2.5
3 3 2 3 2.75 3 3 2 2 2.5   3 3 2 1 2.25
3 3 1 3 2.5  3 3 1 2 2.25  3 3 1 1 2
3 2 3 3 2.75 3 2 3 2 2.5   3 2 3 1 2.25
3 2 2 3 2.5  3 2 2 2 2.25  3 2 2 1 2
3 2 1 3 2.25 3 2 1 2 2     3 2 1 1 1.75
3 1 3 3 2.5  3 1 3 2 2.25  3 1 3 1 2
3 1 2 3 2.25 3 1 2 2 2     3 1 2 1 1.75
3 1 1 3 2    3 1 1 2 1.75  3 1 1 1 1.5
2 3 3 3 2.75 2 3 3 2 2.5   2 3 3 1 2.25
2 3 2 3 2.5  2 3 2 2 2.25  2 3 2 1 2
2 3 1 3 2.25 2 3 1 2 2     2 3 1 1 1.75
2 2 3 3 2.5  2 2 3 2 2.25  2 2 3 1 2
2 2 2 3 2.25 2 2 2 2 2     2 2 2 1 1.75
2 2 1 3 2    2 2 1 2 1.75  2 2 1 1 1.5
2 1 3 3 2.25 2 1 3 2 2     2 1 3 1 1.75
2 1 2 3 2    2 1 2 2 1.75  2 1 2 1 1.5
2 1 1 3 1.75 2 1 1 2 1.5   2 1 1 1 1.25
1 3 3 3 2.5  1 3 3 2 2.25  1 3 3 1 2
1 3 2 3 2.25 1 3 2 2 2     1 3 2 1 1.75
1 3 1 3 2    1 3 1 2 1.75  1 3 1 1 1.5
1 2 3 3 2.25 1 2 3 2 2     1 2 3 1 1.75
1 2 2 3 2    1 2 2 2 1.75  1 2 2 1 1.5
1 2 1 3 1.75 1 2 1 2 1.5   1 2 1 1 1.25
1 1 3 3 2    1 1 3 2 1.75  1 1 3 1 1.5
1 1 2 3 1.75 1 1 2 2 1.5   1 1 2 1 1.25
1 1 1 3 1.5  1 1 1 2 1.25  1 1 1 1 1
```

C Case Study

C.1 Case Study1

C.1.1 Mamdani

```
a=readfis
  ('surprise-mamadani-command.fis');
Out1=evalfis([0.9 0.8 0.9 0.9;
              0.1 0.9 0.1 0.1;
              0.1 0.9 0.1 0.1;
              0.1 0.9 0.1 0.1;
              0.1 0.9 0.1 0.1;
              0.9 0.9 0.5 0.1;
              0.1 0.8 0.1 0.1;
              0.5 0.8 0.1 0.1],a);
out1=
      0.8700
      0.1300
      0.1300
      0.1300
      0.1300
      0.5000
      0.1300
      0.4245
```

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Computing the membership value of the three fuzzy sets.

```
 y1=0;   % little surprise
 y2=0;   % surprise
 y3=0;   % very surprise
if((out>=0) & (out<=0.4))
    y1 = -2.5 * out + 1;
else if((out>=0.1) & (out <=0.5))
    y2 = 2.5 * out - 0.25;
else if((out>=0.5) & (out <=0.9))
    y2 = -2.5 * out + 2.25;
else if((out>=0.6) & (out<=1))
    y3= 2.5 * out - 1.5;
end
```

C.1.2 Sugeno

```
a=readfis
  ('surprise-sugeno-command.fis');
Out1=evalfis([0.9 0.8 0.9 0.9;
              0.1 0.9 0.1 0.1;
              0.1 0.9 0.1 0.1;
              0.1 0.9 0.1 0.1;
              0.1 0.9 0.1 0.1;
              0.9 0.9 0.5 0.1;
              0.1 0.8 0.1 0.1;
              0.5 0.8 0.1 0.1],a);
out =
      0.8750
      0.3000
      0.3000
      0.3000
      0.3000
      0.6000
      0.2750
      0.3750
```

C.1.3 Anfis

```
a=readfis
  ('surprise-anfis-
  aftertrain-minandmethod.fis');
out1=evalfis([0.9 0.8 0.9 0.9;
              0.1 0.9 0.1 0.1;
              0.1 0.9 0.1 0.1;
              0.1 0.9 0.1 0.1;
              0.1 0.9 0.1 0.1;
              0.9 0.9 0.5 0.1;
              0.1 0.8 0.1 0.1;
              0.5 0.8 0.1 0.1],a);
out1 =
       0.9000
       0.4400
       0.4400
       0.4400
       0.4400
       0.6800
       0.4200
       0.5000
```

C.2 Case study2

C.2.1 Mamdani

```
a=readfis
  ('surprise-mamadani-command.fis');
out2=evalfis([0.33 0.5 0.0 0.0;
              0.7 0.5 0.8 0.4;
              0.55 0.5 0.7 0.4;
              0.4 0.5 0.3 0.3;
              1 0.5 0.9 0.9],a);
out2 =
       0.1300
       0.5420
       0.5000
       0.4580
       0.8700
```

C.2.2 Sugeno

```
a=readfis
  ('surprise-sugeno-command.fis');
out2=evalfis([0.33 0.5 0.0 0.0;
              0.7 0.5 0.8 0.4;
              0.55 0.5 0.7 0.4;
              0.4 0.5 0.3 0.3;
              1 0.5 0.9 0.9],a);
out2 =
       0.2075
       0.6000
       0.5375
       0.3750
       0.8250
```

C.2.3 Anfis

```
a=readfis
 ('surprise-anfis-
  aftertrain-minandmethod.fis');
out2=evalfis([0.33 0.5 0.0 0.0;
              0.7 0.5 0.8 0.4;
              0.55 0.5 0.7 0.4;
              0.4 0.5 0.3 0.3;
              1 0.5 0.9 0.9],a);
out2 =
       2.0000
       0.6800
       0.6300
       0.5000
       0.8600
```

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Rui Qiao received her B.S degree in communication engineering and M.S degree in communication and information system both from Wuhan University of Technology, Wuhan, China in July 2002 and July 2005 respectively. She also gained her Ph.D.degree in computer software and theory from Chengdu Institute of Computer Application, Chinese Academy of Sciences, Chengdu, China in July 2008. She is an associate professor at Wuhan University of Science and Technology, Wuhan, China. Her research interests include topics related to formal methods applied to artificial intelligence, and the implementation based on the formalization.

Yajun Feng received the M.S. degree in computer software and theory from PLA University of Science and Technology, Nanjing,China,in 2006. He is a researcher at Air Force Early Warning Academy, Wuhan, China. His research interests include modeling and simulation of complex systems, intelligent optimization algorithms and decision support system.

Xiaolei Zhong gained his M.S.degree in software engineering from Huazhong University of Science and Technology, Wuhan, China in 2012. He is also a researcher at the university. His research interests include embedded system, network of things.

Qiaojia Liu received the B.S. degree in computer science and technology from Tianjin University of Technology and Education in 2003 and M.S. degree in software engineering from Nankai University in 2006. She is a researcher at Tianjin Modern Vocational Technology College, Tianjin, China. Her research interests include object-oriented programming and Android OS.

Heng He gained his M.S.degree in computer architecture and Ph.D.degree in computer application technology both from Huazhong University of Science and Technology, Wuhan, China in 2007 and 2013 respectively. He is also a researcher at Wuhan University of Science and Technology, Wuhan, China. His research interests include multi-agents and cloud computing.

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