This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCDS.2017.2728003, IEEE Transactions on Cognitive and Developmental Systems

Information-Driven Multi-Robot Behavior Adaptation to Emotional Intention in Human-Robot Interaction

Luefeng Chen, *Member, IEEE,* Min Wu, *Senior Member, IEEE,* Mengtian Zhou, Jinhua She, *Senior Member, IEEE,* Fangyan Dong, Kaoru Hirota, *Life Member, IEEE*
Corresponding author: Min Wu (wumin@cug.edu.cn), Tel. & Fax: +86-27-87175075

***Abstract*—To adapt robots' behavior to human emotional intention, an information-driven multi-robot behavior adaptation mechanism is proposed in human-robot interaction. In the mechanism, optimal policy of behavior is selected by information-driven fuzzy friend-Q learning (IDFFQ), and facial expression with identification information are used to understand human emotional intention. It aims to make robots be capable of understanding and adapting their behaviors to human emotional intention, in such a way that human-robot interaction runs smoothly. Simulation experiments are performed according to a scenario of drinking at a bar. Results show that the proposed IDFFQ reduces 51 learning steps compared to the fuzzy production rule based friend-Q learning (FPRFQ), and computational time is about 1/4 of the time consumed in FPRFQ. In Addition, the accuracy of emotion recognition and emotional intention understanding are 80.36% and 85.71%, respectively. The preliminary application experiments are carried out to the developing emotional social robot system (ESRS), and the basic experimental results are shown in the scenario of drinking at a bar with three emotional robots and twelve volunteers.**

***Index Terms*—Behavior Adaptation, Emotional Intention Understanding, Reinforcement Learning, Human-Robot Interaction, Information-Driven**

I. Introduction

As rapidly growing interest of human-robot interaction (HRI) [1], [2], strong and efficient methods of adapting and understanding for robots are greatly requested [3], [4], [5]. Social robot [6], [7], [8] plays an important role in HRI and becomes popular in our daily life, such as home [9], office [10], and even some of them can take care of atypical populations including children and elderly [11], [12]. To facilitate the successful interaction, not only humans, but also robots are required to be capable of adapting to human companions.

In the field of robot learning and adaptation, most researches focus on behavior adaptation of surface-level information. Surface-level information involves verbal and nonverbal communication signals, which can be heard or seen directly during the communication, such as speech [11], gesture [13], and facial expression [14]. But some information cannot be recognized directly, called deep-level information. These kinds of deep-level information mainly include nonverbal communication signals, and they are often tightly coupled to surface-level information that present a kind of complex physiological phenomena, e.g., emotion and intention.

For adaptation to deep-level information. Most of the emotion detection/recognition algorithms are based on static images [15]. Although static emotion recognition has high efficiency and speed, it is susceptible to dynamic information of individual and environment, such as the structure of human facial features, different complexion, light intensity, and so on. Researchers begin to put their interests shifted to the emotion recognition based on dynamic image sequences, it can better describe facial expression because of the expression is a continuous change process. Generally, dynamic emotion recognition methods include feature point tracking method [16], optical flow method [17], motion model approach [18], and so on. Most of the researches are focus on the dynamic image sequence, but cannot directly realize real-time dynamic recognition, also lack of human deep emotional understanding. Emotion no longer stays on the level of recognition in HRI, but is increasingly being applied to determine control policy of behavior adaptation [19], [20]. It endows social robot with artificial emotions [21], which greatly promotes the natural interaction between humans and robots [22]. Taking large scale HRI into consideration, fuzzy production rule based friend-Q learning (FPRFQ) is proposed in our previous researches [24], [25] for behavior adaptation mechanism. Intention understanding is essential for communication and directly links to human deep thinking. An effective way for social robot to facilitate intention understanding is via emotion. Emotion contributes to inform and motivate social decision making, as well as the quality of our social relationships [26]. As rapid development of affective computing, emotional intention understanding receives more and more attention. Behavior emotion is used to understand human intention using network based learning algorithms [27], [28]. Science network learning needs to handle a great deal of calculations, most of intention understanding methods stay in the simulation stage. To promote preliminary application, two-layer fuzzy support vector regression (TLFSVR) is proposed for emotional intention understanding in our previous research [29], where

L. -F. Chen, M. Wu, M. -T. Zhou, and J. She are with the School of Automation, China University of Geosciences, Wuhan, Hubei 430074, China, and Hubei Key Laboratory of Advanced Control and Intelligent Automation for Complex Systems, Wuhan, Hubei 430074, China (e-mail: chenluefeng@cug.edu.cn; wumin@cug.edu.cn).

J. She is also with the School of Engineering, Tokyo University of Technology, Katakura, Hachioji, Tokyo 192-0982, Japan (e-mail: she@stf.teu.ac.jp).

F. -Y. Dong and K. Hirota are with Tokyo Institute of Technology, Nagatsuta, Midori-ku, Yokohama 226-8502, Japan (e-mail: tou.aa@m.titech.ac.jp; hirota@jsps.org.cn).

small data sets are generated by fuzzy c-meas in such a way that it is more effective for fuzzy SVRs. After intention understanding, how robots adapt to human intentions is critical for successful communication.

For solving problems of behavior adaptation in HRI, Q-learning becomes popular. In general, reward/punishment obtained from environment is used to calculate the reward function [30]. For handling the behavior adaptation problems in large HRI, multi-agent reinforcement learning (MARL) [31] is developed, and Q-learning receives a lot of attention [32]. MARL discovers optimal behaviors of autonomous entities (e.g., robots) by using trial-and-error interactions according to the environment. However, the interaction environment is dynamically changing in large HRI. A minimax-Q Learning algorithm is proposed to dynamic environment such as zero-sum games [33]. Moreover, Nash-Q learning and friend-or-foe Q-learning (FFQ) are generated for general-sum games [34], where FFQ is no need to estimates opponents' Q-functions comparing to Nash-Q learning [35]. Most of the researches suppose that robots may achieve their goal by ignoring human emotion, but in HRI, people identification information and deep-level information should be environmental factors, and we consider that MARL can be reconstructed to a more affective way.

For large human-oriented HRI, a behavior adaptation mechanism based on information-driven fuzzy friend-Q learning (IDFFQ) is proposed. Large HRI contains large numbers of humans and robots, that is many humans to many robots, and many always more than three [36]. It aims to adapt multiple robots' behaviors to peoples' intention, and robots' behavior selection is generated by mixed information (i.e., human identification information and Q-values), but not only Q-values. Moreover, intention understanding is realized by using our two-layer fuzzy support vector regression model (TLFSVR) in [29]. With the idea that reward raising as location approaching and satisfaction increasing, reward function is defined by two parts. One is according to the expected location transformed from deep-level information (i.e., emotion and intention), and the other is based on human satisfaction level. According to the proposal, at first, some robots need to obtain people information such as facial expression and identification information (i.e., age, gender, nationality, and religion), which is used to understand deep-level information (i.e., emotion and intention). And then via maximizing their reward according to the deep-level information and Q-values, other robots adaptively adjust their behaviors to emotional intention.

The proposal makes benefits on both sides (i.e., robots and humans) by addressing the robots' response time and humans' satisfaction. Response time (RT) represents time sensitive in robotic tasks collaboration, and indicates potentials of larger scale interaction. For reducing RT, especially for the Muslim, robots may soon pick up non-alcoholic drink according to the religion information while ignoring human intention. Moreover, human satisfaction is the key evaluated index not only for customers' service, but also proposal's practicality in human side. In addition, our proposal emphasizes on human side. Making full use of human identification information (e.g., religion) and deep-level information (e.g., emotion and intention), which will give a big boost to improve relationship between humans and robots. They interacts with each other in such a way that the communication run smoothly.

To validate the proposal, simulation experiments are performed based on a scenario of "drinking at bar". In the scenario, eight volunteers are invited to become customers and express different facial expressions. The training and testing data are collected from eight volunteers, which include photos and questionnaires. Experiments consist of emotion-intention understanding (built by MATLAB and C++ in Visual Studio) and behavior adaptation (designed by MATLAB), which are developed in a PC with dual core processor (2.8GHz), memory (2.99GB), and Windows 7 system. Moreover, to confirm the practicability of the proposal, preliminary application experiments are conducted in the developing emotional social robot system (ESRS). A scenario of "drinking at bar" is performed by twelve postgraduates and three emotional robots in the preliminary application experiments.

The article is arranged as follows. Structure of information-driven fuzzy friend-Q learning (IDFFQ) is introduced in Section II. In Section III, behavior adaptation mechanism based on IDFFQ is proposed and designed in detail. Simulation and application experiments are developed In Section IV.

II. STRUCTURE OF INFORMATION-DRIVEN FUZZY FRIEND-Q LEARNING

To handle the problem of environment uncertainty and large state space, fuzzy production rule based friend-Q learning (FPRFQ) is proposed in our previous study [24]. In the FPRFQ, the discrete lookup Q-table is replaced by "IF-THEN" fuzzy production rules, and generalizes the discrete friend Q-learning to the continuous state space. The updating function is defined as

$$\Delta FQ_{K+1}(s,b_i) = a_k[r_{k+1} - FQ_K(s,b_i) + \gamma \max_{b_i{}'} FQ_K(s', b_i{}')] \tag{1}$$

where i is robot number, b_i is the selective behavior, $a_k \in [0, 1]$ is learning rate, r_k is the reward, $FQ_K(s,b_i) \in$ R is the kth estimate value of the optimal Q-value, $\gamma \in [0, 1]$ is discount factor, $\max_{b_i{}'} FQ_K(s,b_i)$ represents the maximum Q-value of all possible behaviors, and $\Delta FQ_{k+1}(s,b_i) = FQ_{k+1}(s,b_i) - FQ_k(s,b_i)$.

In the HRI, human information may greatly promote the communication, but FPRFQ achieves the goal ignoring some useful human information, for example, identification information such as age and religion. Such information is useful additional information to robots' knowledge, and has great impacts on human habits. Information-driven fuzzy friend-Q learning (IDFFQ) algorithm is introduced to make full use of the human information. In the IDFFQ, behavior selection is generated by mixed information (i.e., human identification information and Q-values), but not only Q-values, as shown in Fig. 1, and mainly consists of four modules.

In the first module, information transfer of the environment information I. The outputs of information transfer module are used as the inputs of IDFFQ. There are two kinds of inputs, including state information I_S (input of IDFFQ) and addition information I_A (for behavior selection).

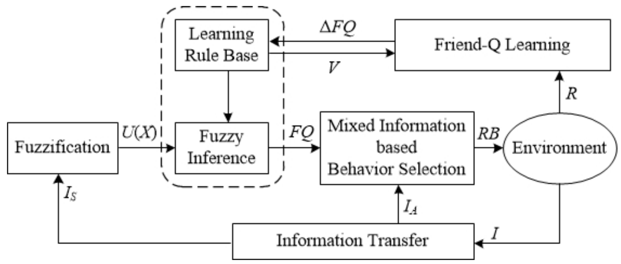


Fig. 1. Structure of information-driven fuzzy friend-Q learning (IDFFQ).

In the second module, fuzzification and fuzzy inference. By using membership function, crisp input set I_S (e.g., human intention and emotion) is fuzzified into linguistic terms of fuzzy sets (e.g., wine of intention, happy of emotion). Via observing the relationship between state and behavior, fuzzy inference using "IF-THEN" fuzzy production rules are designed as

$$\begin{array}{ll} R_i: & If \quad I_S = S_i, \\ & Then \quad RB_j = \{b_{kj} \quad with \quad FQ_{kj}\} \end{array} \tag{2}$$

where *i* is the number of learning rule, S_i is fuzzy state set, and RB_j is behavior set of *j*th robot.

In the third module, behavior selection of robots. The ε-greedy [37] and Boltzmann function [38] are popular explore/exploit policies for generating robots' behaviors. Boltzmann exploration can cover greedy in the case of temperature $T = 0$, while T tends to infinity, behaviors are selected uniformly at random. In the Boltzmann exploration, states of Q-values are the only information for behavior selection. In real HRI application, for example, a robot selects appropriate drink according to customer's religion. In this case, human information have greater influence on behavior selection. Hence, function of Boltzmann exploration is reformulated as

$$p(s, b_i) = \begin{cases} \dfrac{\exp(\max\limits_{b_i} FQ(s,b_i)/T)}{\sum\limits_{i=1}^{n} \exp(FQ(s,b_i)/T)} & I_A = \varphi \\ f(I_A), & I_A \neq \varphi \end{cases} \tag{3}$$

where $p(s,b_i) \in [0, 1]$ is the probability, temperature parameter $T \in R^+$ is decreased over time for decreasing exploration, and $f(I_A)$ is a function or some rules for mapping possibility to addition human information I_A.

In the fourth module, Q-values are calculated according to the reward function by using updating function in (1), and updated to the learning rule base.

III. BEHAVIOR ADAPTATION MECHANISM BASED ON IDFFQ

A. Architecture of Behavior Adaptation Mechanism

The basic idea of the proposed IDFFQ based behavior adaptation mechanism is multiple robots (i.e., information robots and task robots) cooperate with each other to achieve humans' exceptive goal. It reflects the influence of human identification information (i.e., age, gender, nationality, and religion) and deep-level information (i.e., intention and emotion). The architecture consists of two parts including information processing and behavior adaptation, as shown in Fig. 2.

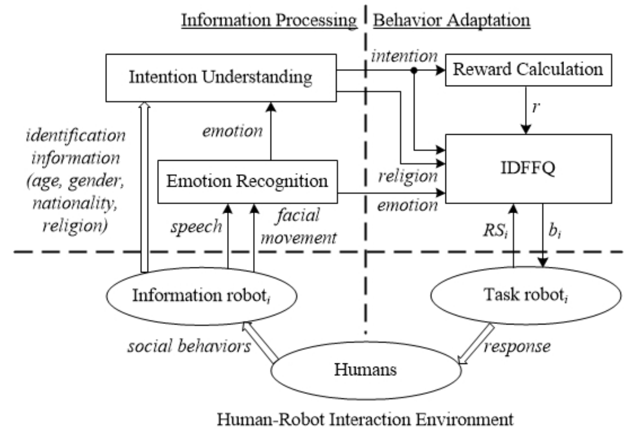


Fig. 2. Architecture of IDFFQ based behavior adaptation mechanism.

Information robots carry out the information processing, which is used to understand humans' social behaviors. Task robots execute the behavior adaptation, including reward calculation and IDFFQ based behavior adaptation.

B. Human Information Processing

1) Emotion Recognition: Emotion is recognized mainly according to the facial expression. By using the Candide3 3D [39] face model, seven basic emotions are recognized according to the facial action units (FAU). Seven basic emotions include happiness, neutral, sad, surprise, fear, disgust, and anger. In the experiments, 6 moving elements are selected from Candide3 model that are the most exaggerated parts among all the FAU as shown in Table I. They include mouth corner lift, upper lip lift, brow lower, outer brow raiser, mouth stretch, and jaw drop, and corresponding to different emotions (FAU in red points) as shown in Fig. 3. Therefore, the facial expressions changes are analyzed by tracking the FAU, and the emotion is obtained in real-time. The extracted motion features of each tracking facial expressions can be represented as

$$f = [T_a(1)^T, T_a(2)^T, T_a(3)^T, \ldots, T_a(L-1)^T, T_a(L)^T]^T \tag{4}$$

where L is the length of the image sequence, T_a is the corresponding parameter, and f is a 6 dimensional feature matrix corresponding to 6 motion units.

TABLE I
FAU UNITS DESCRIBE EMOTIONS

Emotion	FAU
Happiness	Mouth corner lift
Sadness	Brow lower
Anger	Brow lower, jaw drop
Surprise	Outer brow raiser, upper lip lift
Disgust	Upper lip lift, jaw drop
Fear	Mouth stretch

Candide3 based dynamic feature point matching is introduced o identify the seven basic emotions, and is designed as follow,

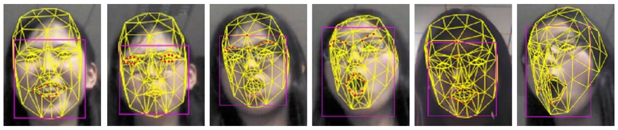


Fig. 3. FAU in red points corresponding to different emotions.

Step 1: Definition of 7 basic emotions $E_1, E_2, \cdots, E_N$, $N = 7$. By using Cadide3, emotion can be defined based on m feature points, and (4) is redefined as $E_i = (e_{i1}, e_{i2}, \cdots, e_{im})$, where $e_{im} \in (-1, 1)$ is the feature points, and $m = 6$.

Step 2: Data preparation. The center of each emotion $\overline{E_i}$ is prepared according to the average value of 6 feature points in the database.

Step 3: Calculation. Based on the formula of Mahalanobis, distance d between the current emotion E and each emotion center $\overline{E_i}$ is Calculate as follow,

$$d^2(E, \overline{E_i}) = (E - \overline{E_i})^T S^{-1} (E - \overline{E_i}) \tag{5}$$

where S is the covariance between E and $\overline{E_i}$.

Step 4: Matching. Emotion E is obtained according to the minimized distance d.

$$\min\{d(E, E_i)\}, i = 1, 2, \cdots N. \tag{6}$$

Step 5: Adjusting. 20 sets of E is selected as a sliding window, if 20 times are the same emotion, E is confirmed, and then output.

2) Emotional Intention Understanding: Based on the emotion with additional information such as age, gender, and nationality, intention understanding aims to comprehend people's inner thoughts in HRI. It is a supported module and realized by using our previous proposed two-layer fuzzy support vector regression (TLFSVR) [29].

Emotion expression seems to reflexively elicit adaptive social responses from others, and conveys information about the evaluation of current desires and intentions. To find the relationship between 7 basic emotions (i.e., happiness, neutral, sad, surprise, fear, disgust, and anger) and order intention (i.e., choice of drinks), twenty-eight volunteers (i.e., different genders people aged 20-65 years, from 6 countries include China, Japan, South Korea, Malaysia, Cuba, and Mexico) are invited in our previous study [29]. According to different emotions, they choose different top seven popular drinks in the Japanese bar (Izakaya), including wine, beer, sake, sour, shochu, whisky, and non-alcoholic drink. At the Izakaya, if the bar tender knows very well about what is the right drink of customer in different emotion, it would be very nice service to the customer. Emotion helps inform and motivate social decision making [40], such as in most of the case, anger with beer, happiness with wine, surprise with sake, and fear with sour in the data collection of the twenty-eight volunteers. Moreover, emotion further triggers behavioral responses. For example, anger can elicit fear related responses or serve as a demand for someone to change their intention, sadness can elicit sympathy, and happy seems to invite social interaction.

C. IDFFQ based Behavior Adaptation Mechanism

1) Reward Function: Reward function is used to evaluate the adaptation level of the task robots, which is calculated according to tasks completed situation of robots and human satisfaction level, and defined as

$$r = \begin{cases} r_t, & \text{simulation} \\ (r_t + r_h)/2, & \text{application} \end{cases}. \tag{7}$$

where r_t represents tasks completed situation, and it is set to 40 (in the case of success), -1 (in the case of mistake), and -40 (in the case of failure); r_h represents human satisfaction level, and it is set to 40 (in the case of very satisfied), 20 (in the case of satisfied), -1 (in the case of normal), -20 (in the case of dissatisfied), and -40 (in the case of very dissatisfied).

For example, in a scenario of drinking at a bar, tasks completed situation is success means robots select the right dink (with highest reward), mistake means the selected drink is not customer's prefer (with encourage reward), and failure means robots select nothing (with punishment).

2) IDFFQ Algorithm: There are 8 steps in the IDFFQ based behavior adaptation mechanism.

Step 1: Parameters initialization.

Temperature parameter *T*, learning step *n*, learning rate α, and discount factor γ are initialized to 1000, N, 1, and 0.99, respectively.

Step 2: Information transfer.

According to Fig. 2, environment information I consists of human intention HI, emotion HE, religion HR, and robot's self state. All of these environment information can be transferred to input states I_S and addition information I_A. For example, there are one information robot and two task robots (i.e., waiter robot and music robot) in the scenario of drinking at the bar. For waiter robot, task is to offer drink service, and its self-state is location RL, then $I_S = \{HI, RL\}$ and $I_A = \{HR\}$; for music robot, task is to play music according to human emotion, and number of playing music is RP, then $I_S = \{HE, RP\}$ and $I_A = \{\phi\}$.

Step 3: Fuzzification.

Crisp values (from 1 to 8) of eight customer's intentions at the bar are fuzzified into the corresponding fuzzy linguistic variables, including "1-wine", "2-beer", "3-sake", "4-sour", "5-shochu", "6-whisky", "7-non-alcoholic drink", "8-others (other drinks or food)",

The triangular and trapezoidal membership function of emotion fuzzy state is obtained by trial and error, as shown in Fig. 4. Emotion is represented in the Pleasure-Arousal plane [41], for "Arousal-Sleep" axis, five linguistic variables are Very Sleep (VS), Sleep (S), Neutral (NT), Arousal (A), and Very Arousal (VA); for "Pleasure-Displeasure" axis, they are Very Displeasure (VD), Displeasure (D), Neutral (NT), Pleasure (P), and Very Pleasure (VP).

Step 4: Fuzzy inference

For waiter robot, since location can be related to customer's 8 intentions, 64 (8×8) fuzzy rules are designed as

$$\begin{aligned} &If \quad I_S = \{HI \quad and \quad RL\}, \\ &Then \quad RB_j = \{b_{kj} \quad with \quad FQ_{kj}\}. \end{aligned} \tag{8}$$

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCDS.2017.2728003, IEEE Transactions on Cognitive and Developmental Systems

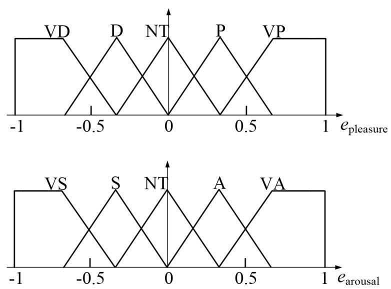


Fig. 4. Membership function of emotion plane.

For music robot, based on the previous study of emotion and music [42], 4 kinds of violin music are used to express 7 basic emotions (i.e., happiness, surprise, fear, disgust, sadness, anger, and neutral). Hence, 28 (7×4) fuzzy rules are detail designed as

$$\begin{array}{l} If \quad I_S = \{HE \quad and \quad RP\}, \\ Then \quad RB_j = \{b_{kj} \quad with \quad FQ_{kj}\}. \end{array} \tag{9}$$

Step 5: Behavior selection.

For waiter robot, behavior is selected based on human religion HR and Q-values. According to the information of illegal for alcohol with Islam religion, (3) is detail designed as follow,

$$p(s, b_i) = \begin{cases} \dfrac{\exp(\max\limits_{b_i} FQ(s,b_i)/T)}{\sum\limits_{i=1}^{n} \exp(FQ(s,b_i)/T)}, & HR \neq \text{Muslim} \\ 0, \quad HR = \text{Muslim}\& \neq \min\limits_{b_i}(RL'_i - \overline{HR}) \\ 1, \quad HR = \text{Muslim}\& \min\limits_{b_i}(RL'_i - \overline{HR}) \end{cases} \tag{10}$$

where $RL'_i \in \{1, 2, 3, 4, 5, 6, 7, 8\}$ is robot's location, and $\overline{HR}$ is set to "7-non-alcoholic drink" as the Muslim intention.

For music robot, behavior with highest Q-value has more possibility to be selected.

Step 6: Update of Q-values.

By using updating function (1), the Q-value of the selective behavior in each robot is updated and saved to the learning rule base.

Step 7: Learning will stop if $RL =$ place of $HI/\overline{HR}$ (for waiter robot) or $RP =$kind of HE (for music robot), and the best learning behavior b_l^* of each robot is outputted; else jump to Step 8.

Step 8: Let $n = n + 1$. If learning step $n < N$, then jump to Step 2; else jump to Step 1.

IV. EXPERIMENTS ON BEHAVIOR ADAPTATION TO INTENTION

A. Experiment Preparation

1) Experiment Setting: Experiments are developed based on the scenario of "drinking at a bar". Not only because bar is one of the typical communication situations, but also it is very hot in all over world and has another form in Japan, called Izakaya. Izakaya is very popular for the salary man to promote friendship after work, and enjoying the time in Izakaya becomes one part of their life. Understanding and adapting to customer intention at the bar is an effective way to increase revenues and smooth communication. For intention understanding, two-layer fuzzy support vector regression (TLFSVR) model based intention understanding model is proposed in our previous study [29]. For intention adaptation, based on identification information (i.e., religion) and deep-level information (i.e., intention and emotion), our goal of experiments is to adapt service robots' behaviors to customers' order intentions at a bar.

At a bar, customers always drink alcohol and enjoy music, which indicates drink and music are two necessities of a bar. According to this basic idea, the scenario of "drinking at a bar" may consist of one information robot (for understanding customers' emotion and intention) and two service robots (one is waiter robot for selecting drinks according to customers' intention and the other is music robot for playing music to adapt to customers' emotion). Simulation experiments consist of emotion-intention understanding and behavior adaptation experiments. Emotion-intention understanding experiments simulate the jobs of the information robot, where emotion recognition is developed by C++ in Visual Studio and intention understanding is created by MATLAB. Behavior adaptation experiments simulate the jobs of the task robots, in which the waiter robot selects drinks according to human intention and music robot plays songs according to human emotion. Behavior adaptation experiments are built by MATLAB, and the environment is a PC with a dual core processor (2.8GHz), memory (2.99GB), and Windows 7 system.

2) Self-Built Data: Eight volunteers are invited to build the data sample of emotion recognition, and they express seven basic emotions such as happiness, surprise, fear, neutral, disgust, sadness, and anger, totally 56 emotions are shown in Fig. 5. They are from four countries (i.e., China, Japan, South Korea, and Malaysia) with different genders in Tokyo, and Malaysian is Islam religion. Moreover, experiment uses seven basic emotions for recognition because they are dispersedly distributed in four quadrants of Pleasure-Arousal plane as shown in Fig. 6, where seven discrete basic emotion is mapped to the central point of the seven small block in the plane.

Fig. 5. Volunteers emotion.

Twenty-two volunteers are asked to build up data sample of intention understanding. They are required to write down identification information such as age, gender, nationality, and religion, and complete questionnaires about the relationship between 25 kinds of emotion (e.g., happiness, surprise, fear,

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCDS.2017.2728003, IEEE Transactions on Cognitive and Developmental Systems

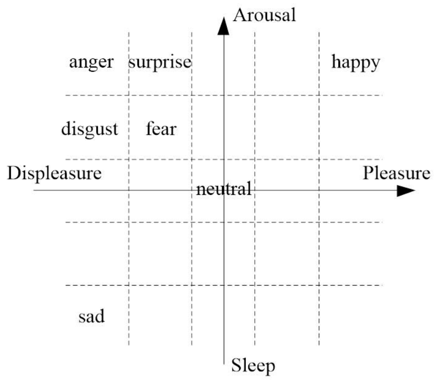


Fig. 6. Pleasure-Arousal emotion plan.

etc.) and 8 intentions (i.e., wine, beer, sake, sour, shochu, whisky, non-alcoholic drink, and other drinks or food) to order at a bar. A total of 406 groups of data are collected, where 350 groups for training and 56 groups (data corresponding to seven basic emotions in eight volunteers) for testing, as shown in Fig. 7 and Fig. 8 (groups of data includes information of emotion, age, gender, nationality/religion, and intention).

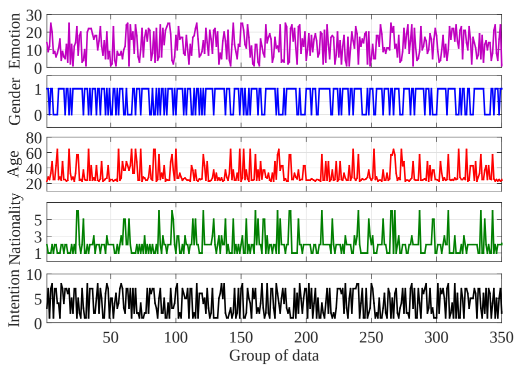


Fig. 7. Training data for intention understanding.

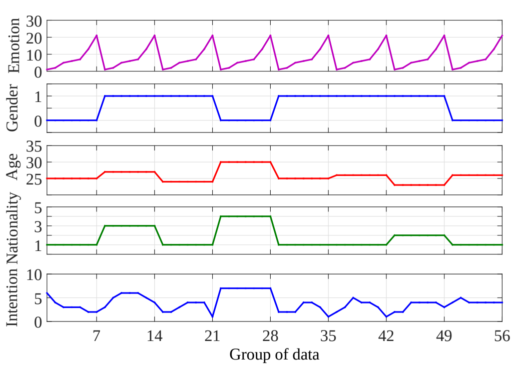


Fig. 8. Testing data of eight volunteers for intention understanding.

According to the most popular drinks at the Izakaya, searching map is designed for behavior adaptation, as shown in Fig. 9, where dashed box is start point and black boxes are forbidden areas; human intentions from 1 to 8 means "1-wine", "2-beer", "3-sake", "4-sour", "5-shochu", "6-whisky", "7-non-alcoholic drink", and "8-others (other drinks or food) ".

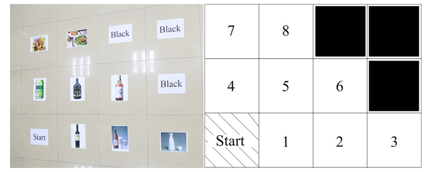


Fig. 9. Searching map.

B. Experiments on Emotion-Intention Understanding

Emotion recognition and intention understanding are developed to support experiments of behavior adaptation. Emotion recognition is mainly based on the facial expression, and realized via capturing, extracting, and analyzing the size and shape of eyes and mouth. The experimental result for 56 emotional photos of 8 volunteers is shown in Fig. 10. According to data analyses, numbers of correctly recognized photos are 45, wrong recognized photos are 8, and failed recognized photos are 3, totally recognition rate is 80.36%. Compared to the Euclidean distance based feature point matching (EDFPM) [16], the recognition rete of the proposed Candide3 based dynamic feature point matching (CDFPM) is 7.15% higher than that of EDFPM. This is because the proposed CDFPM is based on Mahalanobis distance, which is unitless and scale-invariant. Science Mahalanobis distance takes into account correlations of data set, it can find out the variation of main feature points in facial expression, in such a way that improving emotion recognition rate.

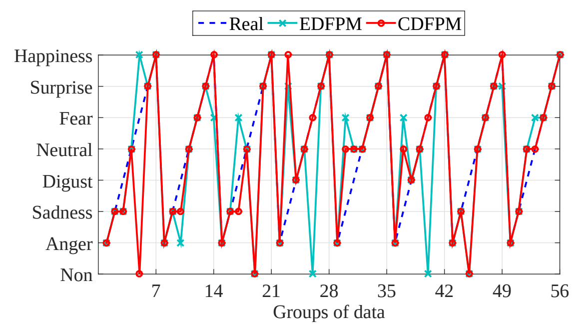


Fig. 10. Result of emotion recognition rate.

In the intention understanding experiments, inputs are emotion and identification information (i.e., age, gender, and nationality). Based on two-layer fuzzy support vector regression (TLFSVR) [29], intention understanding mainly includes two parts. One part is FCM based data clustering, where the clusters number is chosen as 2 according to the gender of female and male, the sensitivity threshold and the overlap constant are selected to 3 and 1, respectively; the other part is multi-SVR learning, where Gaussian kernel width and scalar regularization parameter are set to 0.5 and 200, respectively. According to the data analysis of result in Fig. 11, the understand accuracy of TLFSVR is 85.71%, and the correlation of output and real value is 0.9362, where high correlation indicates that the TLFSVR based intention understanding model can well reflect the actual situation. Moreover, we compared the results to random SVRs (RSVRs) [23], and intention understanding accuracy is 7.14 % lower than that of our proposed TLFSVR. Since features of the identification information is obvious in the scenario of "drinking at a bar", such as gender and nationality are clear distinction in general. In the case of obvious features, information features based clustering in proposed TLFSVR is more efficient than data subset by randomly selecting in RSVRs.

C. Experiment on Behavior Adaptation to Intention

To validate the performance of the proposal, based on the senior of drinking at the bar, experiments on the proposed IDFFQ is carried out to compared with the FPRFQ [24].

According to the experimental setting, there are two service robots, including waiter robot and music robot. For waiter robot, the task is to select drinks according to customers' intentions. According to searching map in Fig. 9, 8 kinds of customers' intentions are "1-wine", "2-beer", "3-sake", "4-sour", "5-shochu", "6-whisky", "7-non-alcoholic drink", and "8-others (other drinks or food)", and 5 kinds of behaviors are "left", "right","up", "down", and "pick up". For music robot, the task is to play music to adapt to customers' emotion, and 4 violin music are used to express 7 basic emotions, where neutral by 1-"Canon in D"; happiness by 2-"4th movement (Ode to Joy)"; sadness by 3-"Castle in the Sky"; fear,surprise, disgust, and anger by 4-"Caprice No. 2". In such a way that, music robot does the only behavior "playing next", and follows the sequence of "1-2-3-4-1". Completing a task for waiter robot means adapting until ordering is same as customer's intention, and for music robot means the playing music is the one reflects customer's emotion.

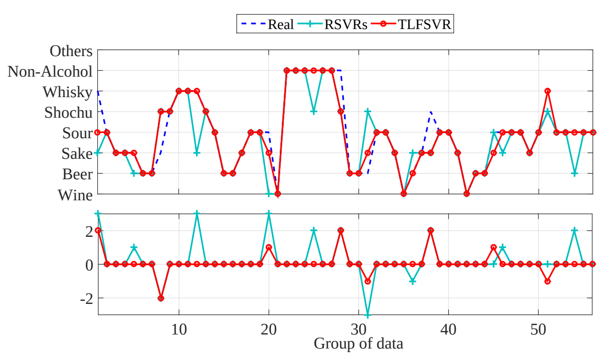


Fig. 11. Result of intention understanding accuracy.

In each algorithm, for guaranteeing optimal policy, temperature parameter T is set to 1000; the discounted parameter γ and the learning rate α (initial value = 1) are set to 0.99 and $1/(1+\alpha)^4$ (decreasing function), respectively. In one simulation, each algorithm repeated twice and 5000 rounds.

Based on the adaptation results in Fig. 12, Fig. 13, and Fig. 14, the data analysis is given in Table II, where average learning steps of IDFFQ is 51 steps less and average reward is 3 times bigger than those of FPRFQ. Moreover, by using our proposal, robot's response time (defined by computational time) is about 1.12s, which saves 3.09s than that of FPRFQ (i.e., about 1/4 of the time consumed in FPRFQ).

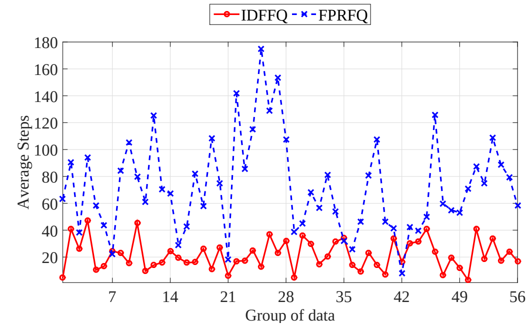


Fig. 12. Average steps of completing a task.

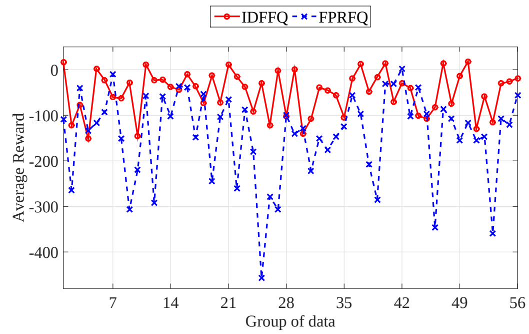


Fig. 13. Average reward of completing a task.

Because of two reasons, our proposal obtains smaller response time. On the one hand, information robot is added to collect and understand human intention and emotion, in another word, instead of understanding each customer's intention one by one, task robots get the human information directly via information robot. On the other hand, identification information (i.e., religion) is embedded into task robot for behavior selection, especially for Muslims, with the useful information of religion, task robot can quickly adjust the goal to non-alcoholic drink. For example, 22nd-28th groups of data in Fig. 12-Fig. 14 belong to Muslims volunteer, science the religion information in the proposed IDFFQ is provided in (10), leading to less learning steps and higher reword than those of the FPRFQ.

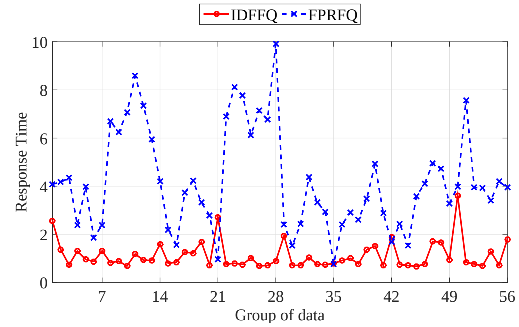


Fig. 14. Average computational time of completing a task.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCDS.2017.2728003, IEEE Transactions on Cognitive and Developmental Systems

TABLE II
COMPARATIVE RESULTS OF ADAPTATION ALGORITHMS

index	IDFFQ/FPRFQ		
	Mean	Min	Max
Average steps	22/73	3/8	43/175
Average reward	-49/-145	-152/-457	18/1.8
Average computational time (s)	1.12/4.21	0.67/0.76	3.60/9.91

D. Preliminary Application Experiments in Emotional Social Robot System (ESRS)

A scenario of "drinking at a bar" is performed in the developing ESRS to verify the practicability of the proposal, where 12 volunteers and three emotional robots including waiter mobile robot, information mobile robot, and music robot. ESRS is a two-layer network system as shown in Fig. 15, which is divided into the bottom layer-information sensing and transfer layer, and the top layer-intelligent computation layer. 12 volunteers are postgraduates from different ages (20-30), genders (3 females and 9 males), areas (of China and Jordan), and religion (Islam) in our lab, as shown in Fig. 16.

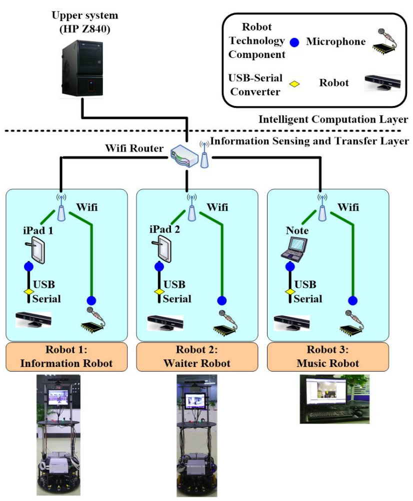


Fig. 15. Network of ESRS.

The customer's intentions contain 8 kinds as mentioned in the experiment setting, and seven primary emotions are used for facial expression. Robot will fail to recognize beyond the scope of the seven primary emotions, and the experimental environment is shown in Fig. 17.

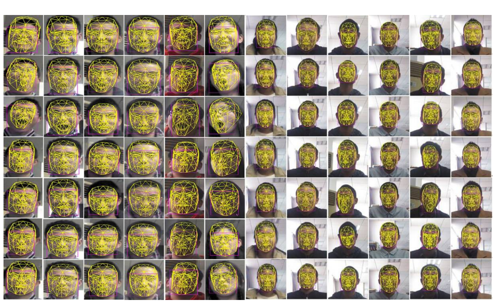


Fig. 16. 12 volunteers.

Fig. 17. Experimental environment.

After knowing the emotional intention by information robot, waiter robot will go to pick up the drink that reflect customer's intention, and there are 5 kinds of behaviors, including left, right, up, down, and pick up. For instance, while expressing "Sadness" emotion, the information robot will understand the customer's order intention is "Beer", then the waiter robot will go to pick up "Beer" from "Start", as shown in Fig. 18.

The results of emotion-intention understanding are shown in Table III, which shows that dynamic emotion recognition receives 80.1% recognition rate and 77.4% for intention understanding. Based on the waiter robot's performance, 12 customers give the satisfaction level S in five levels, i.e., "1-very dissatisfied", "2-dissatisfied", "3-normal", "4-satisfied", and "5-very satisfied". Questionnaires are designed in Table IV, where satisfaction level S_1 in question 1 (for evaluating the understanding accuracy) is according to customer's answer, such as "yes" for "5-very satisfied" and "no" for "1-very dissatisfied". For question 2 (for evaluating the enjoyment of the service), satisfaction level S_2 is described as five answers refer to five satisfaction levels, respectively. The total satisfaction level is represented by $S = [(S_1 + S_2)/2]$.

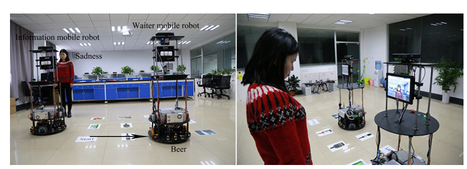


Fig. 18. Robot behaviors adaptation to "Sadness" emotional intention.

According to the results in Table V, 12 volunteers' average satisfaction level is "4-satisfied", especially for the Muslim volunteer, he can avoid alcohol drink no matter what kind of emotion, which leads higher understanding accuracy and enjoyment by using the proposed IDFFQ than that of FPRFQ. Moreover, an one-way ANOVA is used to represent the statistical significations of the response in Table V, which aims to determine whether different accuracy (of intention understanding)/enjoyment are significantly different from each other by comparing the means of them. Both of the two methods have equal impact on accuracy and enjoyment, which is set as the null hypothesis. According to result of ANOVA in

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TCDS.2017.2728003, IEEE Transactions on Cognitive and Developmental Systems

TABLE III
RESULTS OF EMOTION RECOGNITION AND INTENTION UNDERSTANDING

Emotion Recognition		Intention Understanding	
Emotion	Recognition Rate	Intention	Understanding Rate
Happy	11/12	Wine	12/16
Sadness	7/12	Beer	14/18
Angry	10/12	Sake	4/6
Surprise	11/12	Sour	3/4
Disgust	10/12	Shochu	6/7
Fear	9/12	Whisky	9/12
Neutral	10/12	Non-alcoholic	11/13
		Others	6/8
Average	80.1%	Average	77.4%

TABLE IV
QUESTIONNAIRES FOR CUSTOMERS' FEEDBACK

Questions	Answers
Accuracy: 1. Is the order you want in your mind?	1-Yes, 2-no
Enjoyment: 2. How much is your satisfaction?	1-very bad, 2-bad, 3-normal , 4-good, 5-very good

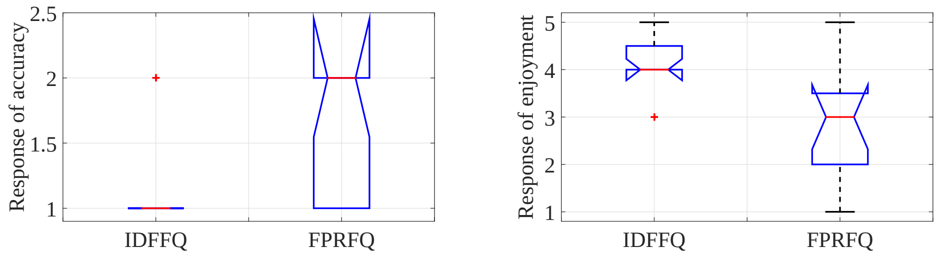
TABLE V
RESPONSE OF QUESTIONNAIRES

Volunteer	Waiter robot served drinks by IDFFQ/FPRFQ in ESRS		
	Responses for accuracy	Responses for enjoyment	Satisfaction level
1	1/1	4/4	4.5/4.5
2	2/1	3/3	2/4
3	1/2	5/1	5/1
4	1/2	4/3	4.5/2
5	1/1	4/4	4.5/4.5
6	2/2	3/1	2/1
7	1/1	4/3	4.5/4
8	1/2	4/3	4.5/2
9	1/2	5/5	5/3
10	1/2	4/3	4.5/2
11	1/1	4/3	4.5/4
12	1/2	5/1	5/1
Average (satisfaction)	4.3/2.7	4.1/2.8	4.2/2.75

Fig. 19 and Table VI, the null hypothesis needs to be rejected since all the P-values are lower than 0.05, in another word, different methods have signification impact on accuracy and enjoyment, which indicates the effective of the our proposal.

According to the description of large HRI, that is many humans to many robots (many means more than three) [36]. Science there are 12 volunteers and 3 mobile robots in the preliminary experiment on the scenario of "drinking at a bar", it can be regarded as large HRI. Compared the emotion recognition result in the simulation (80.36%) and application (80.1%), they are very close. This is because the control units of our mobile robots are industrial personal computer, which is ARK-3500 with quad-core processor (2.7GHz), memory (4GB), and Windows 7 system. The system and program environment are the same as the PC for simulation, which can guarantee the accuracy of emotion recognition from the experimental setting and has enough processing speed for dealing with the large HRI; moreover, in our scenario, no matter how many humans, customers firstly should communicate with the information robot (as guider), then the information robot will recognize the human emotion and share the information to other robots via wifi. The sharing information mechanism can make the communication more smoothly, in such a way that the accuracy of emotion recognition can be guaranteed even in the large HRI.

In the case of not high accuracy of emotion recognition, such as some misrecognition in the application as shown in Table III, that may lead to misunderstand the human intention. However, there are two ways to handle this problem in our proposal. One is that performance of robots' behaviors is evaluated by human satisfaction. Robot will receive reward (positive in success, and negative in unsuccess) and human satisfaction level (positive in satisfaction, and negative in dissatisfaction). With these guiders, in the case of emotion misrecognition (lead to intention misunderstanding), robot cannot once fulfill the task, but try to learn several times to reach human expectation; The other is that robots select behaviors based on the human identification information. Especially for Muslims, regardless of the human emotion, robots can quickly adjust the goal to non-alcoholic drink with the useful



(a) Boxplots of accuracy by different methods

(b) Boxplots of enjoyment by different methods

Fig. 19. Boxplots of responses by different methods

TABLE VI
ANOVA SUMMARY OF (a)/(b) IN FIG. 19

Source	SS	df	MS	F	$\mathrm{P_{rob}} > \mathrm{F}$
Columns	1.04167/9.375	1/1	1.04167/9.375	5/9.13	0.0358/0.0063
Error	4.58333/22.5833	22/22	0.20833/1.02652		
Total	5.625/31.9583	23/23			

religion information. In addition, typical human identification information includes not only Muslims, our proposal also considers other information. For example 12 volunteers in the application experiment, they are from different provinces of China (including Hubei, Shanxi, and Hebei province). Science people in different provinces may have their own habit, and behavior selection of robots can be guided by human, they can learn this habit step by step until they satisfy human intention.

For further interesting research, combination of the social robots and internet becomes popular, adaptation mechanism for internet robot will be interesting [44]. For real application, some information based behavior reinforcement learning algorithms are developed to some social robots. For example, Peper [45] learns together with children at home environment and Nao [46] grasps an object with left hand according to human cognitive information. These methods indicate that the proposed IDFFQ based behavior adaptation mechanism would be available to behavior adaptation of social robots in HRI.

V. Conclusion

The behavior adaptation mechanism based on information-driven fuzzy friend-Q learning is proposed. To verify the proposed mechanism, comparative experiments between the proposal and fuzzy production rule based friend-Q learning [24] are developed.

According to experiment results, with the human information, robot response time becomes smaller and average satisfaction level of customers is ”satisfied”, in such a way that a human-oriented smooth human-robot interaction is obtained. There are two points for reducing time, one is that information robot is added to collect and understand human intention and emotion, in another word, instead of understanding each customer’s intention one by one, task robots get the human information directly via information robot; the other is that identification information (i.e., religion) is embedded into task robots for behavior selection, especially for Muslims, with the useful information of religion, task robots can quickly adjust the goal to non-alcoholic drink. In addition, high satisfaction comes from quickly correct service by waiter robot, and enjoyable violin music by music robot.

Based on our verification experiments and some successful application cases (e.g., Pepper [45] and Nao [46]) by using information-driven reinforcement learning algorithms, our proposed IDFFQ based behavior adaptation mechanism can be developed for behavior adaptation of social robot in human-robot interaction.

Acknowledgment

This work was supported in part by the National Natural Science Foundation of China under Grants 61603356 and 61210011, the 111 Project under Grant B17040, the Hubei Provincial Natural Science Foundation of China under Grant 2015CFA010, and the Fundamental Research Funds for the Central Universities, China University of Geosciences (Wuhan) (No. 201548).

References

[1] S. Sheikhi and J. M. Odobez, “Combining dynamic head pose-gaze mapping with the robot conversational state for attention recognition in human-robot interactions,” *Pattern Recognition Letters*, Vol. 66, pp. 81-90, 2015.

[2] D. Y. Y. Sim and C. K. Loo, “Extensive assessment and evaluation methodologies on assistive social robots for modelling human-robot interaction - A review,” *Information Sciences*, Vol. 301, pp. 305-344, 2015.

[3] S. Ikemoto, H. B. Amor, T. Minato, B. Jung, and H. Ishiguro, “Physical human-robot interaction: mutual learning and adaptation,” *IEEE Robotics & Automation Magazine*, Vol. 19, No. 4, pp. 24-35, 2012.

[4] F. J. Abu-Dakka, B. Nemec, J. A. Jørgensen, T. R. Savarimuthu, N. Krüger, and A. Ude, “Adaptation of manipulation skills in physical contact with the environment to reference force profiles,” *Autonomous Robots*, Vol. 39, pp. 199-217, 2015.

[5] H. Zhang, P. Wu, A. Beck, Z. -J. Zhang, and X. -Y. Gao, “Adaptive incremental learning of image semantics with application to social robot,” *Neurocomputing*, Vol. 173, pp. 93-101, 2016.

[6] A. Sciutti, L. Patan, F. Nori, and G. Sandini, “Understanding object weight from human and humanoid lifting actions,” *IEEE Transactions on Autonomous Mental Development*, Vol. 6, NO. 2, pp. 80-92, 2014.

[7] F. Chersi, “Learning through imitation: a biological approach to robotics,” *IEEE Transactions on Autonomous Mental Development*, Vol. 4, No. 3, pp. 204-214, 2012.

[8] Y. -N. Li, K. -P. Tee, W. -L. Chan, R. Yan, Y. -W. Chua, and D. K. Limbu, "Continuous role adaptation for human-robot shared control," *IEEE Transactions on Robotics*, Vol. 31, NO. 3, pp. 672-681, 2015.

[9] K. G. Kim, D. Choi, J. -Y. Lee, J. -M. Park, and B. -J. You, "Controlling a humanoid robot in home environment with a cognitive architecture," in *Processings of IEEE International Conference on Robotics and Biomimetics*, Phuket, Thailand, 2011, pp. 1754-1759.

[10] N. Mitssunaga, T. Miyashita, H. Ishiguro, K. Kogure, and N. Hagita, "Robovie-IV: a communication robot interacting with people eaily in an office," in *Proceedings of International Conference on Intelligent Robots and System*, Beijing, China, 2006, pp. 5066-5072.

[11] J. Wainer, B. Robins, F. Amirabdollahian, and K. Dautenhahn, "Using the humanoid robot KASPAR to autonomously play triadic games and facilitate collaborative play among children with autism," *IEEE Transactions on Autonomous Mental Development*, Vol. 6, NO. 3, pp. 183-199, 2014.

[12] T. Shimizu, R. Saegusa, S. Ikemoto, H. Ishiguro, and G. Metta, "Robust sensorimotor representation to physical interaction changes in humanoid motion learning," *IEEE Transactions on Neural Networks and Learning Systems*, Vol. 26, NO. 5, pp. 1035-1947, 2015.

[13] E. A. Sisbot, L. F. M. Urias X. Broqure, D. Sidobre, and R. Alami, "Synthesizing robot motions adapted to human presence," *International Journal of Social Robotics*, VoL. 2, No. 3, pp. 329-343, 2010.

[14] V. Tikhanoff, A. Cangelosi, and G. Metta, "Integration of speech and action in humanoid robots: iCub simulation experiments", *IEEE Transactions on Autonomous Mental Development*, Vol. 3, No. 1, pp. 17-29, 2011.

[15] I. Kotsia, I. Pitas, "Facial Expression Recognition in Image Sequences Using Geometric Deformation Features and Support Vector Machines," *IEEE Transactions on Image Processing*, 16(1): 172-187, 2007.

[16] E. Vezzetti, F. Marcolin, G. Fracastoro, "3D face recognition: An automatic strategy based on geometrical descriptors and landmarks," *Robotics and Autonomous Systems*, 62(12): 1768-1776, 2014.

[17] C. K. Hsieh, S. H. Lai, Y. C. Chen, "An Optical Flow-Based Approach to Robust Face Recognition Under Expression Variations," *IEEE Transactions on Image Processing*, 19(1): 233-240, 2010.

[18] S. M. Xiang, F. P. Nie, C. S. Zhang, "Learning a Mahalanobis distance metric for data clustering and classification," *Pattern Recognition*, 41: 3600-3612, 2008.

[19] C. Yu, M.-j. Zhang, F.-h. Ren, and G.-z. Tan, "Emotional multiagent reinforcement learning in spatial social dilemmas," *IEEE Transactions on Neural Networks and Learning Systems*, Vol. 26, NO. 12, pp. 3083-3096, 2015.

[20] P. Barros, D. Jirak, C. Weber, and S. Wermter, "Multimodal emotional state recognition using sequence-dependent deep hierarchical features," *Neural Networks*, Vol. 72, pp. 140-151, 2015.

[21] J. Novikova and L. Watts, "Towards artificial emotions to assist social coordination in HRI", *International Journal of Social Robotics*, Vol. 7, No. 1, pp. 77-88, 2015.

[22] J. Su, "Promoting interactions between humans and robots using robotic emotional behavior", *IEEE Transactions on Cybernetics*, Vol. 46, No. 12, pp. 2911-2923, 2016.

[23] O. Garcia-Hinde, V. Gomez-Verdejo, M. Martinez-Ramon, C. Casanova-Mateoa, J. Sanz-Justo, S. Jimenez-Fernandez, and S. Salcedo-Sanz, "Feature selection in Solar Radiation prediction using Bootstrapped SVRs", in *Proceedings of IEEE Congress on Evolutionary Computation (CEC)* , Vancouver, Canada, 2016, pp. 3638-3645.

[24] L. -F. Chen, Z. -T. Liu, F. -Y. Dong, Y. Yamazaki, M. Wu, and K. Hirota, "Adapting multi-robot behavior to communication atmosphere in humans-robots interaction using fuzzy production rule based friend-Q learning", *Journal of Advanced Computational Intelligence and Intelligent Informatics*, Vol. 17, No. 2, pp. 291-301, 2013.

[25] L. -F. Chen, Z. -T. Liu, M. Wu, F. -Y. Dong, Y. Yamazaki, and K. Hirota, "Multi-robot behavior adaptation to local and global communication atmosphere in humans-robots interaction," *Journal on Multimodal User Interfaces*, vol. 8, no. 3, pp. 289-303, 2014.

[26] M. Coeckelbergh, "Are emotional robots deceptive?", *IEEE Transactions on Affective Computing*, Vol. 3, No. 4, pp. 388-393, 2012.

[27] X. Li, Y. Pan, G. Chen, and H.Yu, "Adaptive human-robot interaction control for robots driven by series elastic actuators", *IEEE Transactions on Robotics*, 2016.

[28] J. -H. Han, S. -J. Lee, and J. -H. Kim, "Behavior hierarchy-based affordance map for recognition of human intention and its application to human-robot interaction", *IEEE Transactions on Human-Machine Systems*, Vol. 46, No. 5, pp. 708-722, 2016.

[29] L. -F. Chen, Z. -T. Liu, M. Wu, M. Ding, F. -Y. Dong, Y. Yamazaki, and K. Hirota, "Emotion-age-gender-nationality based intention understanding in human-robot interaction using two-layer fuzzy support vector regression," *International Journal of Social Robotics*, Vol. 7, No. 5, pp. 709-729, 2015.

[30] J. Kober and J. Peters, "Reinforcement learning in robotics: a survey," *Reinforcement Learning*, Springer Berlin Heidelberg, pp. 579-610, 2012.

[31] L. Busoniu1, R. Babuska, and B. D. Schutter, "Multi-agent reinforcement learning: an overview," *Innovations in Multi-Agent Systems and Applications-1*, Springer Berlin Heidelberg, pp. 183-221, 2010.

[32] M. L. Littman, "Markov games as a framework for multi-agent reinforcement learning," in *Proceedings of the 11th international conference on machine learning*, New Brunswick, USA, 1994, pp. 157-163.

[33] J. Hu and M. P. Wellman, "Nash Q-learning for general-sum stochastic games," *Journal of Machine Learning Research*, Vol. 4, pp. 1039-1069, 2003.

[34] M. L. Littman, "Friend-or-foe Q-learning in general-sum games," in *Proceedings of Eighteenth International Conference on Machine Learning*, Massachusetts, America, 2001, pp. 322-328.

[35] C. J. H. Watkins and P. Dayan, "Q-learning", *Machine Learning*, Vol. 8, No. 3-4, pp. 279-292, 1992.

[36] A. Kolling, P. Walker, N. Chakraborty, K. Sycara, and M. Lewis, "Human Interaction With Robot Swarms: A Survey," *IEEE Transactions on Human-Machine Systems*, Vol. 46, No. 1, pp. 9-26, 2015.

[37] L. P. Kaelbling, M. L. Littman, and A. W. Moore, "Reinforcement learning: a survey," *Journal of Artificial Intelligence Research*, Vol. 4, pp. 237-285, 1996.

[38] S. Singh, T. Jaakkola, M. Littman, and C. Szepesvari, "Convergence results for single-step on-policy reinforcement-learning algorithms," *Machine Learning*, Vol. 38, No. 3, pp. 287-308, 2000.

[39] J. Ahlberg, "Model-based coding: extraction, coding, and evaluation of face model parameters," Ph.D. dissertation, Linkoping University, Linkoping, Sweden, No.761, 2002.

[40] D. Keltner and J. Haidt, "Social functions of emotions at four levels of anysis," *Cognition and Emotion*, Vol. 13, No. 5, pp. 505C521, 1999.

[41] Z. -T. Liu, M. Wu, D. -Y. Li, L. -F. Chen, F. -Y. Dong, Y. Yamazaki, and K. Hirota, "Concept of fuzzy atmosfield for representing communication atmosphere and its application to humans-robots interaction," *Journal of Advanced Computational Intelligence and Intelligent Informatics*, Vol. 17, No. 1, pp. 3-17, 2013.

[42] Z. -T. Liu, Z. Mu, L. -F. Chen, et al., "Emotion recognition of violin music based on strings music theory for mascot robot system," in *Proceedings of the 9th International Conference on Informatics in Control*, Automation and Robotics, Rome, Italy, 2012, pp. 5-14.

[43] H. A. Vu, Y. Yamazaki, F. -Y. Dong, and K. Hirota, "Emotion recognition based on human gesture and speech information using RT middleware," in *Proceedings of IEEE International Conference on Fuzzy Systems*, Taipei, Taiwan, 2011, pp. 787-791.

[44] J. Su, "Representation and inference of user intention for internet robot", *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, Vol. 44, No. 8, pp. 995-1002, 2014.

[45] S. Calinon, P. Kormushev, and D. G. Caldwell, "Pepper learns together with children: development of an educational application," in *Proceedings of IEEE-RAS 15th International Conference on Humaniod Robots*, Seoul, Korea, 2015, pp. 270-275.

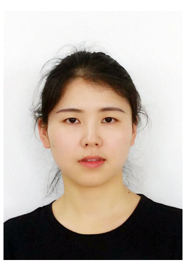
[46] M. Richter, Y. Sandamirskaya, and G. Schoner, "A robotic architecture for action selection and behavioral organization inspired by human cognition," in *Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems*, Algarve, Portugal, 2012, pp. 2457-2464.

Luefeng Chen (M'16) received the Ph.D. degree of Engineer in computation intelligence and systems science from Tokyo Institute of Technology, Japan, in 2015, and the B.S. degree in automation as well as M.S. degree in control science and engineering from Central South University, China, in 2009 and 2012, respectively. Science 2015, he has been a lecture in the School of Automation, China University of Geosciences, Wuhan, China. His research interests include computational intelligence, human-robot interaction, machine learning, emotion recognition and understanding, fuzzy logic, and fuzzy clustering.

Dr. Chen is a member of Chinese Association for Artificial Intelligence, Chinese Association of Automation, and Japan Society for Fuzzy Theory and Intelligent Informatics. He received Best Paper Award in ASPIRE League Symposium 2012 and Young Researcher Award of JACIII in 2014.

Min Wu (SM'08) received the B.S. and M.S. degrees in engineering from Central South University, Changsha, China, in 1983 and 1986, respectively, and the Ph.D. degree in engineering from the Tokyo Institute of Technology, Tokyo, Japan, in 1999. He was a faculty member of the School of Information Science and Engineering at Central South University from 1986 to 2014, attaining the position of full professor. In 2014, he moved to the China University of Geosciences, Wuhan, China, where he is a professor in the School of Automation. He was a visiting scholar with the Department of Electrical Engineering, Tohoku University, Sendai, Japan, from 1989 to 1990, and a visiting research scholar with the Department of Control and Systems Engineering, Tokyo Institute of Technology, from 1996 to 1999. He was a visiting professor at the School of Mechanical, Materials, Manufacturing Engineering and Management, University of Nottingham, Nottingham, UK, from 2001 to 2002. His current research interests include robust control and its applications, process control, and intelligent control.

Dr. Wu is a Member of the Chinese Association of Automation. He received the IFAC Control Engineering Practice Prize Paper Award in 1999 (together with M. Nakano and J. She).



Mentian Zhou received the B.Sc. degree from Yangtze University, China, in 2015. She is currently pursuing M.Sc. degree in the School of Automation, China University of Geosciences, Wuhan, China. Her research interest covers emotion recognition, intention understanding, and human-robot interaction.

Jinhua She (M'94-SM'08) received the B.S. degree in engineering from Central South University, Changsha, China, in 1983 and the M.S. and Ph.D. degrees in engineering from the Tokyo Institute of Technology, Tokyo, Japan, in 1990 and 1993, respectively.

In 1993, he joined the School of Engineering, Tokyo University of Technology, where he is currently a Professor. His research interests include the application of control theory, repetitive control, process control, Internet-based engineering education, and robotics.

Dr. She is a member of the Society of Instrument and Control Engineers, the Institute of Electrical Engineers of Japan, the Japan Society of Mechanical Engineers, and the Asian Control Association. He received the International Federation of Automatic Control (IFAC) Control Engineering Practice Paper Prize in 1999 (jointly with M. Wu and M. Nakano).

Fangyan Dong received Ph.D. degree from Tokyo Institute of Technology in 2003. She is an associate professor in Tokyo Institute of Technology, Japan. Her research interests include computational intelligence, logistics optimization, kansei engineering, and intelligent robot.

Dr. Dong is members of Japan Society for Fuzzy Theory and Intelligent Informatics and Japanese Society for Artificial Intelligence.

Kaoru Hirota (LM'16) received Dr. E. degrees from Tokyo Institute of Technology in 1979.

He is an honourary professor in Tokyo Institute of Technology, Japan. His research interests include fuzzy systems, intelligent robot, and image understanding.

Dr. Hirota experienced president and fellow of IFSA (International Fuzzy Systems Association), and president of SOFT (Japan Society for Fuzzy Theory and Systems). He is a chief editor of J. of Advanced Computational Intelligence and Intelligent Informatics. Banki Donat Medal, Henri Coanda Medal, Grigore MOISIL Award, SOFT best paper award, Acoustical Society of Japan best paper award, were awarded to him. He organized more than 10 international conferences/symposiums as a founding/general/program chair.