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A Robot Emotion Model with History

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Abstract— **In this paper, we present a novel robot emotion model that can be used for social robots engaged in human-robot interactions (HRI). The proposed model effectively determines the robot's emotional state based on its own emotion history, the affect of the user whom the robot is interacting with, and the HRI task at hand. The model uniquely uses an n^{th} order Markov Model (MM) to track the robot's emotion history during interactions. Simulated experiments were conducted using the robot emotion model to persuade different users to comply with various tasks. The results showed that the model is able to effectively determine a robot's emotion based on different input scenarios. Furthermore, the novel use of emotion history allows the robot emotion model to be trained faster.**

Index Terms— ***robot emotions, human-robot-interaction, n^{th} order Markov model, emotional history***

I. Introduction

The majority of social robots are expected to interact with humans using natural interfaces, such as speech, facial expressions and body language, rather than the traditional human-computer interfaces such as keyboard, mouse or joystick. By employing such natural communication interfaces, social robots are able to provide more comfortable and user-friendly assistance [1].

From the several features that can enhance a robot's social interfaces, emotions are of special interest. Robots with emotional intelligence can respond appropriately to diverse scenarios: when helping users that may show signs of distress or anxiety; when persuading people to perform a task, such as taking medicine; or even when contacting professional help for the user [2]. Emotions can facilitate bidirectional communication, which is perceived as natural and more engaging by the user [3]. They can also make users relate to the robot and to feel more secure during the interaction [4].

This paper presents a novel robot emotion model with emotional history for task-based HRI. By employing a n^{th} order Markov model, our model can account for a varying number of past robot emotions. This approach is different from other emotion models which only consider a single past emotion, or that only react to the user's immediate actions without regard to previous robot emotions. The robot emotional history and the user's affect are used by the emotion model to learn the appropriate emotions to display when interacting with users for a variety of different social tasks.

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II. Robot Emotion Models

A handful of computational models for robot emotions have been developed for social robots. These models can be classified as: 1) decision lists or look-up tables [5]–[7], 2) Bayesian networks [4], [8]–[12], and 3) Markov models (MM) [3], [13], [14].

In [6], a receptionist robot with four emotions (joy, sadness, disgust, and anger) was used to help visitors. The user could interact with the robot using a keyboard. After the user typed a sentence, the robot would provide a verbal response and display an emotion obtained from a decision list. The emotion would be displayed by the robot's virtual face and would last for the duration of the robot's verbal response. The emotion was generated based solely on the user input.

The companion robot presented in [8] is able to interact with people using gestures, sound and lights to display six emotions (happiness, sadness, disgust, surprise, anger, and fear). It uses three pressure sensors to detect human touch on its body, and one microphone to detect features of speech (i.e. harmonics, amplitude, pitch, tempo, and envelope). When the user interacts with the robot by touching or speaking to it, these inputs are fed into two Dynamic Bayesian Network: the first estimates the overall love probability; and the second generates the emotional states. The outputs of both networks are fused by an Artificial Neural Network to produce the outputs for the locomotion, light, audio and body-gesture systems.

Markov models represent a popular method for modeling emotions. These models determine the emotion based on the emotion from the previous time instant [3], [13], [14]. In [14], a cooperative multiagent robot team used a MM to generate emotions for each individual robot. While cleaning the floor, two robots could engage in interaction and use four emotions (joy, anger, fear, and sad) to help them allocate tasks. To generate an emotion that accurately describes the robot's state, the emotional state transition matrix is updated based on the perception system through some basic variables, such as energy level, barrier level, and workload. This application was tested through simulation, in which the robot team successfully allocated tasks to clean the floor.

The majority of the aforementioned models determine the current emotion based solely on the user's current input. A few

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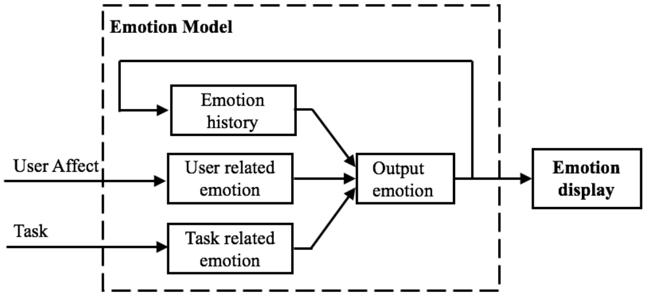


Fig. 1. Robot Emotion Model

approaches also consider the previous robot emotional state. Our work proposes an emotional model that employs an n^{th} order Markov model to represent the robot's previous emotional history over multiple interactions. It also allows the generation of displayed emotions that are consistent with the recent experience of the robot. The emotional history simulates the decay of emotions as time passes by, which is a similar characteristic of human emotions [15].

III. Robot Emotion Model

The proposed robot emotion model, shown in Fig. 1, determines the current robot emotion based on its emotional history, the affect of the user, and task that needs to be completed. The model for the robot's emotional state at time t, E_t', for m robot emotions and l tasks is represented as:

$$\boldsymbol{E_t} = w_1\boldsymbol{H_t} + W_2\boldsymbol{A_t} + W_3\boldsymbol{K_t}, \tag{1}$$

$$E_t' = f(\boldsymbol{E_t}), \tag{2}$$

where $\boldsymbol{E_t}$ is the robot emotion output vector, and $\boldsymbol{H_t}$ is the robot emotional state vector based on the emotional history for time t. $\boldsymbol{A_t}$ represents the human affect input vector, and $\boldsymbol{K_t}$ is the task input vector. w_1 is a scalar which represents the weight of the influence of the robot emotional history on the current emotion, W_2 represents the robot emotion state-human affect probability distribution, and W_3 presents the robot emotional state-task probability distribution. $f(\boldsymbol{E_t})$ represents a winner takes all function, which is used to determine the emotion for the robot to display.

A. Robot Emotion History Model

The robot's emotional state for an n^{th} order MM satisfies the following property when the history information considered is n [2]:

$$P(H_t = e_0 | H_{t-1} = e_1, \dots, H_1 = e_{t-1}) = \tag{3}$$
$$P(H_t = e_0 | H_{t-1} = e_1, \dots, H_{t-n} = e_n),$$

where $e_0, \dots, e_t \in \{1, \dots, m\}$ are the emotions displayed by the robot.

The influence of a given past emotion should decrease as time passes [15]. To achieve this behavior, a decay function is used to reduce the weight of each past emotion in discrete time:

$$\lambda_i = e^{-ai}, 0 < a < -\ln(\varepsilon), \tag{4}$$

where λ_i is the weight for the emotion at discrete time $i \in T^+$, a is the rate of decay, and $n = \lceil T \rceil - 1$. The lower threshold of the decay function is given by ε.

The robot emotion transition probability is modeled as:

$$P(H_t = e_0 | H_{t-1} = e_1, \dots, H_{t-n} = e_n) = \sum_{i=1}^{n} \lambda_i q_{e_i e_0}, \tag{5}$$

where $q_{e_i e_0}$ is an element of Q_i, which is the $m \times m$ robot emotion transition probability. This model can be represented in matrix form as:

$$\boldsymbol{H_t} = \sum_{i=1}^{n} \lambda_i Q_i \boldsymbol{H_{t-i}}\,. \tag{6}$$

Since we cannot calculate Q_i directly, it is necessary to perform an estimation. To this end, the transition frequency $f_{kj}^{(i)}$ from emotional state j to emotional state k is considered with history i:

$$F^{(i)} = \begin{pmatrix} f_{11}^{(i)} & \cdots & f_{1m}^{(i)} \\ \vdots & \ddots & \vdots \\ f_{m1}^{(i)} & \cdots & f_{mm}^{(i)} \end{pmatrix}. \tag{7}$$

Therefore, the estimation of Q_i is represented as:

$$\widehat{Q_i} = \begin{pmatrix} \hat{q}_{11}^{(i)} & \cdots & \hat{q}_{1m}^{(i)} \\ \vdots & \ddots & \vdots \\ \hat{q}_{m1}^{(i)} & \cdots & \hat{q}_{mm}^{(i)} \end{pmatrix}, \tag{8}$$

where $q_{kj}^{(i)}$ is given by:

$$q_{kj}^{(i)} = \begin{cases} \dfrac{f_{kj}^{(i)}}{\sum_{j=1}^{m} f_{kj}^{(i)}} & \text{if } \sum_{j=1}^{m} f_{kj}^{(i)} \neq 0 \\ 0 & \text{otherwise}\,. \end{cases} \tag{9}$$

B. User Affect

The robot emotion state-human affect probability distribution matrix W_2 can be determined from training data. For this paper, we obtained this matrix from the training data obtained from the HRI experiments we conducted in [4].

C. Task Distribution Update

A dynamic reward is used to train the robot's emotional state-task probability distribution W_3:

$$W_3 = W_3' - \Omega C, \tag{10}$$

where W_3' is a $m \times l$ matrix that represents the likelihood of user compliance for each robot emotion, Ω is a scalar weight, and C is a $m \times l$ matrix containing the frequency of each robot emotion displayed during the execution of a task.

When performing a task $x \in \{0, \dots, l\}$, the robot will interact with the user by displaying an emotion e while asking the user to comply with the task. If the robot succeeds (task compliance), a positive reward will be given to the corresponding element w_{3ex}' of W_3'; otherwise, a negative reward will be given. This allows the robot to learn the emotions that have the most likelihood of obtaining user compliance.

To minimize the repeated occurrence of a dominant emotion which will not satisfy the task for a specific user, an emotion counter C is used to reduce the probability of the previous emotions that have been displayed by the robot. Each time the robot displays an emotion e during the task x, the corresponding element c_{ex} of C is incremented. The influence of C is given by Ω. If $c_{ex} = 1$, then Ω receives a positive reward; otherwise, if $C_{ex} > 1$, it will receive a negative reward due to the repetition.

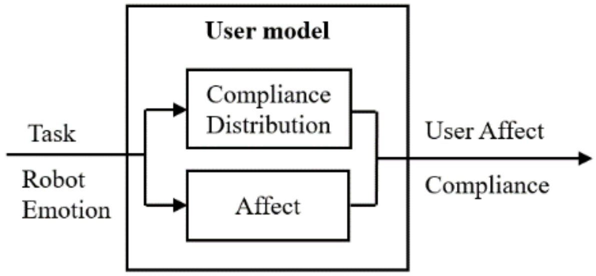


Fig. 2. User Model

The update of W_3 is recorded only during training and not during implementation. By doing this, the robot can avoid being personalized for only one single user.

IV. Simulated Experiments

To evaluate the robot emotion model, we performed simulated HRI experiments between a virtual robot and virtual users. The objective of the simulated experiments was to investigate: 1) the influence of robot emotion history on determining appropriate emotions, and 2) the ability of the model to effectively adapt the emotions based on its own emotional history, user affect, and the task at hand to persuade the user to comply.

A. Experimental Design

The designed interaction scenario consisted of a robot trying to persuade a user to comply with different daily tasks. Each user responded to the robot regarding his/her compliance to participate in the task. If the user had complied, then the task was completed and the robot would start the next task. If the user had not complied, then the robot would continue to persuade the user until the user complied with that task.

1) Emotional States

For these experiments, we selected a set of three positive (high valence) and three negative (low valence) emotions with different intensities [16], as well the "neutral" emotion, totaling $m = 7$ emotional states. The positive emotional states are {excited, happy, interested}, whereas the negative ones are {worried, sad, stern}. These emotional states were also used to define the virtual users' affect.

2) User Model

Each user model consisted of two components: 1) a compliance distribution, and 2) user affect, as shown in Fig. 2.

The compliance distribution S contains the probability of each robot emotion e obtaining the user's compliance for each task. This determines whether the user has complied with the emotion $\boldsymbol{E}_t'$ displayed by the robot.

The user affect $\boldsymbol{A}_{t+1}'$ is a combination of the interaction between the user and the robot during a given task, thus being dependent on both $\boldsymbol{E}_t'$ and $\boldsymbol{K}_t$. The user affect is represented as follows:

$$\boldsymbol{A}_{t+1}' = B_1\boldsymbol{E}_t' + B_2\boldsymbol{K}_t, \quad (11)$$

$$A_{t+1} = f(\boldsymbol{A}_{t+1}'), \quad (12)$$

where B_1 is the probability transition matrix used to generate user affect–robot emotion transition for a given robot emotion, $\boldsymbol{E}_t'$, and B_2 is the transition matrix used to generate user affect-task, $\boldsymbol{K}_t$. B_1 and B_2 are different for each user. A winner takes all function, $f(\boldsymbol{A}_{t+1}')$, is used to determine the output user affect, A_{t+1}.

3) User Personality

Three different personalities P_p, $p \in [1,2,3]$ were considered for the user models, where each personality has a different compliance distribution, B_1 and B_2. Each user interacting with the robot is represented as:

$$U = P_p + \alpha \times r, \quad (13)$$

where r is a $l \times m$ uniform random noise matrix, and each of the matrix elements has a range of $(0,1)$. Additionally, α, where $0 < \alpha < 1$, is a weight representing the influence of the random matrix. The addition of random noise provides variability between users.

4) Tasks

Three tasks were chosen to highlight interaction scenarios with the robot focusing on everyday activities. The tasks were selected from different areas of daily life.

- Task 1: Ask users to go to the movies.
- Task 2: Ask users to invite family over.
- Task 3: Ask users to exercise.

B. Experimental Results

To evaluate the proposed emotion model, two experiments were performed. In Experiment 1, the model was trained with different values of n to investigate the influence of emotion history on convergence. In Experiment 2, the trained models obtained from Experiment 1 were tested with a distinct set of users to assess the performance of each trained model.

1) Experiment 1

The emotion model was trained with varying lengths of robot emotion history (i.e. for different values of n). Namely, 150 different users were used for the training based on the three personalities, 50 for each personality type, for the three different tasks with $n \in \{1,5,10\}$.

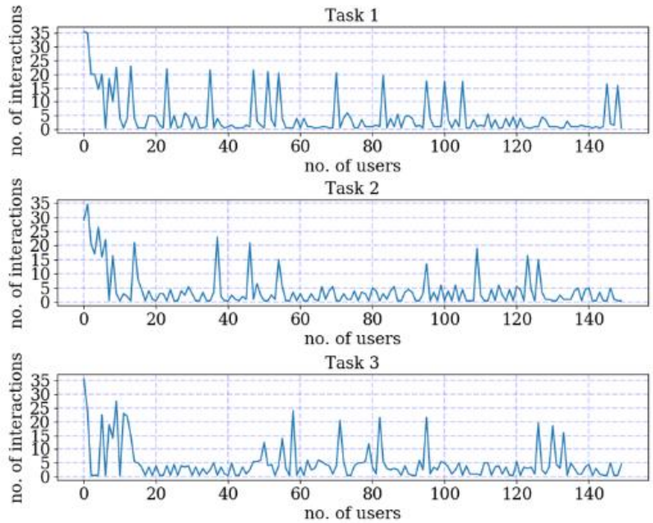
For the first case, when $n = 1$, the emotion history is modeled as a 1st order Markov model, and only a single previous robot emotion is considered. For the second and third case, $n = 5, 10$, the emotion history is modeled as a 5th and 10th order Markov model.

The results are presented in Fig. 3. In the first case, where $n = 1$, the model still needs a large number of interactions (i.e. up to 20) to get users' compliance, even after being trained with a significant number of users. Hence, the model with these large number of users still does not converge.

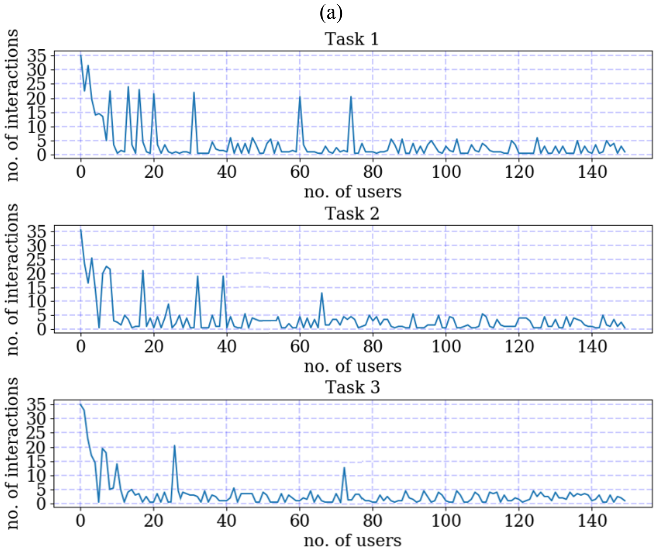
In the second case, with $n = 5$, the system converged to 5 interactions after interacting with 150 users. In the third case, where $n = 10$, the system converged to 3 interactions at approximately 45 users, exhibiting a faster convergence rate due to the increase of the history length.

2) Experiment 2

After training, the model was tested with 150 new users who were not used in the training. In real-world interactions human behaviour is non-deterministic, hence users may not always comply when the robot displays the users' expected emotions, which was identified through the training. To represent such



(a)



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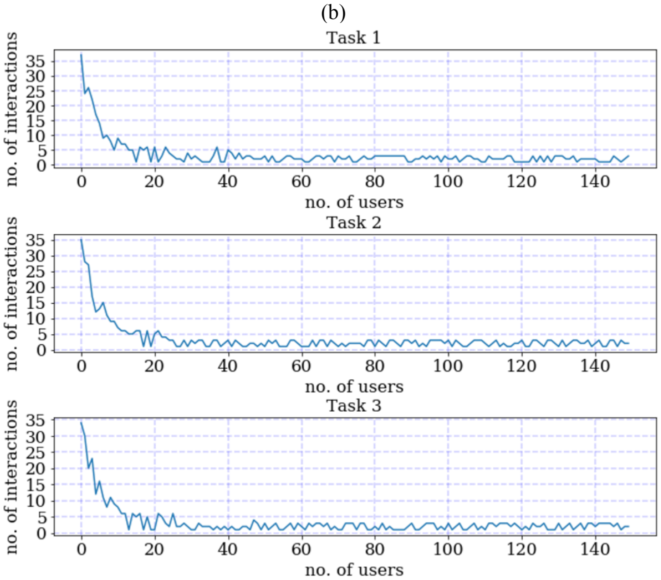
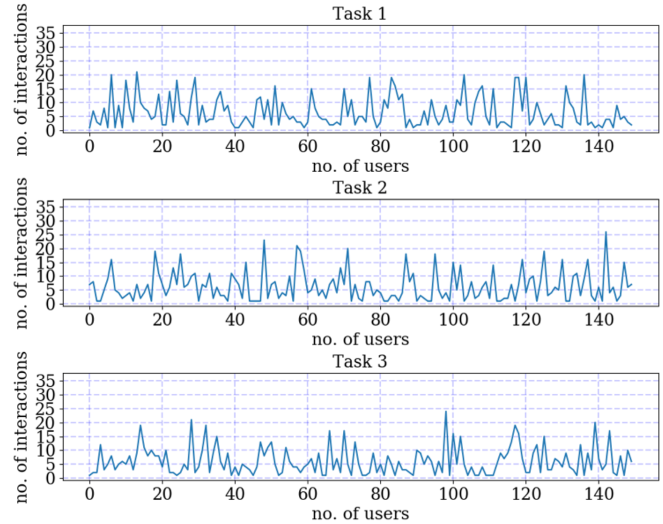
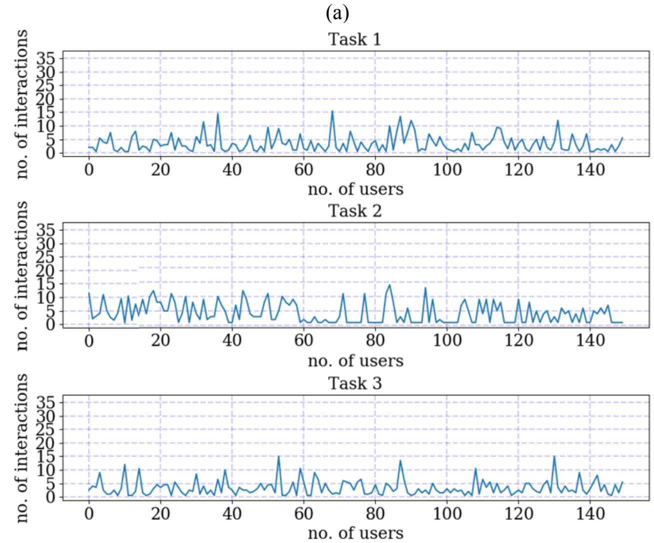


(c)

Fig. 3. Emotion model trained with varying history lengths: (a) $n = 1$, (b) $n = 5$, (c) $n = 10$.



(a)



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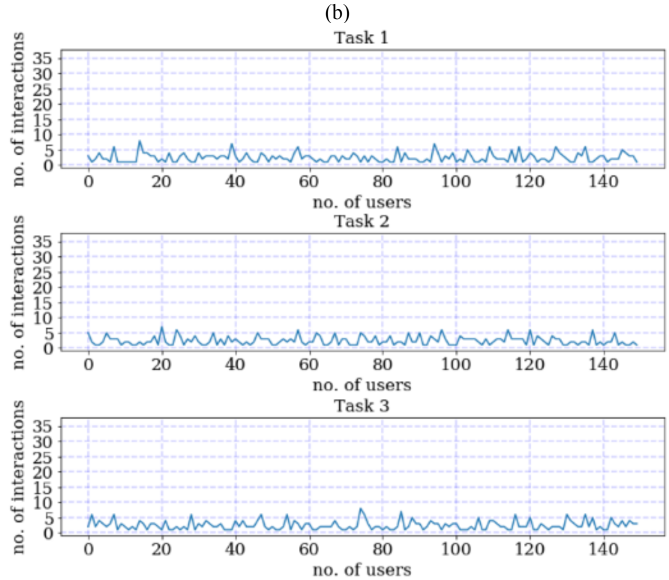

(c)

Fig. 4. Emotion model tested with varying history lengths: (a) $n = 1$, (b) $n = 5$, (c) $n = 10$.

TABLE I
MEAN AND STANDARD DEVIATION FOR TESTING GROUP

		Task 1	Task 2	Task 3	Average
$n = 1$	Mean	6.5	5.6	6.1	6.1
	SD	5.5	5.2	5.0	5.2
$n = 5$	Mean	3.9	3.5	3.9	3.8
	SD	3.3	3.3	3.3	3.3
$n = 10$	Mean	2.5	2.4	2.5	2.5
	SD	1.5	1.4	1.5	1.5

behavior, the compliance for each interaction with the expected emotion was represented as 90% for all users. The percentage of users $\beta(d)$ who comply with the expected emotion in $d \geq 1$ interactions is:

$$\beta(d) = 9 \times 10^{2-d}\% \,. \tag{14}$$

The robot emotion model was tested with $n = \{1, 5, 10\}$, as shown in Fig. 4. The mean and standard deviation are presented in Table I, where it is possible to see that these values are significantly smaller for $n = 10$ than for $n = 1$ and $n = 5$. This demonstrates that the emotional history has a positive influence on the convergence rate and performance of the model.

The robot's ability to change its emotion based on the inputs is presented in Fig. 5. Namely, Fig. 5(a)-(j) shows the detailed robot emotions for a random set of 10 users. These examples provide a good representation of the robot's ability to change its emotion based on the inputs as well as its own emotional history in order to persuade the user. For example, in Fig. 5(a), when the robot tried to persuade the user to go to the movies (Task 1), the robot was initially in the emotional state of neutral. As the human's affect changed from neutral to interested, the robot's emotion changed to happy, at which time the robot persuaded the user successfully.

V. Conclusion

This paper presents a novel robot emotion model which takes into account the robot's emotional history for task driven HRI scenarios. The proposed model allows the robot to choose the

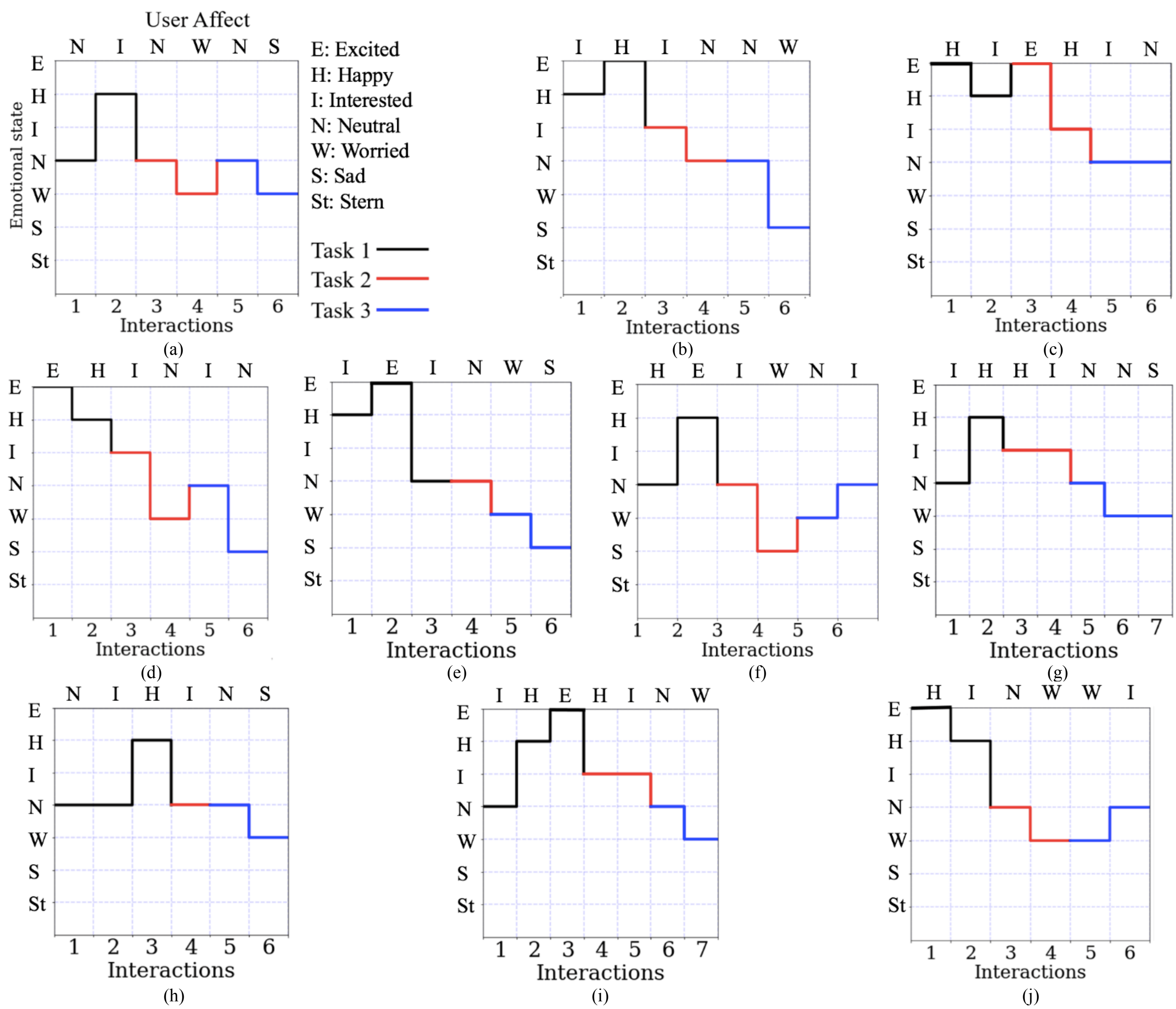

Fig. 5. Robot emotions during interactions with a sub-set of users

appropriate emotion based on (a) its own emotional history, (b) the user's affect, and (c) the task. In our approach, the emotional history is modelled using an n^{th} order MM.

Simulated experiments were performed to investigate the ability of the emotion model to adapt the robot's emotion based on the user affect to complete the task. Experimental results showed that the robot is able to adapt its emotions and effectively persuade the user to comply with the given task. The results also indicate that a faster convergence can be achieved with more emotion history. Future work will focus on implementing the proposed model into a physical social robot to perform guidance tasks with human users.

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