# Empathic Interaction using the Computational Emotion Model

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***Abstract*— This paper describes the empathy oriented human-robot interaction model. It is projected to design the model capable of different empathic responses (parallel and reactive) during the course of interaction with the user, depending upon the personality and mood factors of the robot. The proposed model encompasses three main stages i.e., perception, empathic appraisal and empathic expression. Perception refers to capturing user's emotion state via facial expression recognition. Empathic appraisal is based on the computational emotional model for generating its internal emotions, mood state and empathic responses. The internal emotions are defined using psychological studies and generated on 2D (pleasure-arousal) scaling model; whereas, fuzzy logic is used to calculate the intensity of the each emotion. A virtual facial expression simulator is applied for expression of resultant empathic emotions. Preliminary experimental results show that the proposed model is capable of exhibiting different empathic responses with respect to the personality and mood factors.**

## I. INTRODUCTION

With the increasing use of robots in daily life, the research on the interaction between human and robot is getting much attention. The robots are not only required to perform general tasks with intelligence, but they are also expected to be equipped with social intelligence for better human-robot interaction. Among other challenges of social intelligence, one is to establish the empathic interaction between human and robot. Empathic interaction refers to the ability to detect the user's affective state and to respond to it in an empathic manner. Such interaction is believed to enhance supportive and communicative social skills of robots in human-robot interaction [1].

In human social interaction, empathy promotes pro-social and cooperative behavior leading to moral acts like helping, caring, and justice [2]. Empathy allows individuals to share the affective states of others, predict ones' actions, and stimulate pro-social behavior. Earlier research indicate the presence of similarity of social behavior between human-human and human-robot interactions [3]–[5]. Moreover, several studies discussed that the presence of empathic emotion in a robot has significant positive effects on a user's impression of robot and friendly relationship between human and robot [1] [5]-[7].

Empathy refers to a communicative process in which we understand and respond to the feelings of other person [8]. Davis [9] defines empathy as: "*set of constructs that connects the responses of one individual to the experiences of another.*" He further classifies two kinds of empathy based on the different empathic outcomes such as parallel empathy and reactive empathy. In parallel empathy the response contains the similar emotion to that the other person is experiencing. The reactive empathy, on the other hand, is a response to the experience of other person that may differ from the observed affect. The outcome of reactive empathy is further divided into two different responses. One is sympathy or empathic concern, another is personal distress. Individuals who can self-regulate increase in their emotional arousal are more likely to respond with sympathy and sympathy focuses on reducing some of the other person's distress [10]. In general, the sympathy is positively related to prosocial behavior, whereas personal distress is negatively related to prosocial behavior [11]. Thus, in this paper, sympathy is regarded as a reactive response.

Davis [9] refers to individual differences in the tendency to experience different reactive responses (sympathy and personal distress) to the distress of other person. Personality is one of the key factors to construct the individual differences, such as perception, motivation and cognition [12], [13]. Moreover, the differences of personality will influence and intervene to individual psychological phenomena, for instance, apprehension of emotions and

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emotional behaviors. Among several models of personality, one of the widely accepted personality models is five factors (Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism) model that is proposed by McCrae and Costa [14]. The results of the study of associations between personality dimensions and empathy also confirmed positive associations between agreeableness, openness and neuroticism to experience and empathy [15]. Table I shows the five factors of personality and its descriptions. The personality and mood are directly affected over the different type empathic response [16]. However, the mood condition appears to be a stronger predictor of empathy, with personality in the interaction terms by enhancing the power of mood. [16]. In agreement with the psychological theories mentioned earlier, the proposed model is introduced with parallel and reactive responses of empathy. We have implemented a computational emotion model that is equipped with its own mood state and emotions along with the robot personality factors to characterize the robot as an individual. The expressions of empathic response using facial expressions are performed through the virtual facial expression simulator called Grimace [17].

The main contribution of this paper is modeling of the empathic responses in human-robot interaction, which is based on psychological theory by Davis [9]; where it is intended to generate the empathic emotions based on two different empathic responses (parallel and reactive) by regulating internal mood and emotions.

This paper is divided as follows: Section II explains the different stages of the proposed empathic interaction model. Section III presents the results of the initial experiment that was conducted to observe the behavior of the model by showing the empathic responses. Finally, the conclusion is stated in section IV.

TABLE I: Five Factors of Personality [14]

| Factor | Description |
|---|---|
| Openness | Open mindedness, interest in culture |
| Conscientiousness | Organized, persistent in achieving goals |
| Extraversion | Preference and behavior in social situations |
| Agreeableness | Interactions with others |
| Neuroticism | Tendency to experience negative thoughts |

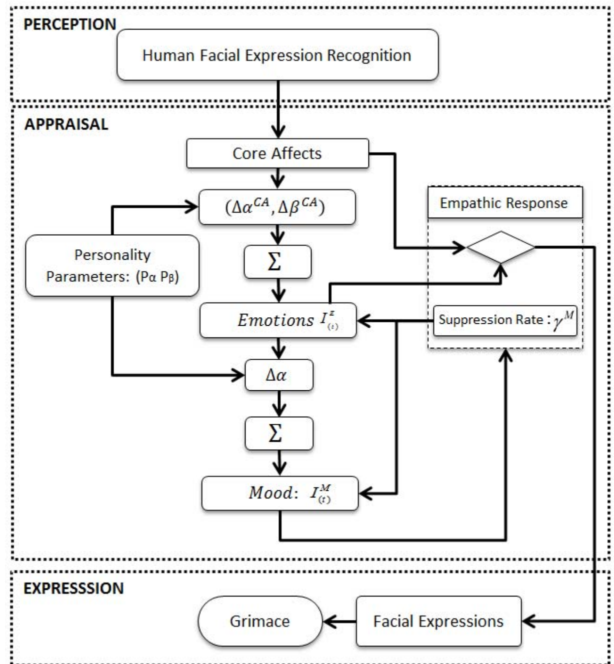


Fig. 1: Structure and stages of the Empathic Interaction Model

## II. EMPATHIC INTERACTION MODEL

The proposed empathic interaction model is illustrated in Fig. 1. It mainly consists of three stages; perception, appraisal and expression of empathy. Perception is the first stage of the model and it refers to understanding emotions of the user. The facial expressions play an important part in interaction by expressing and communicating emotions [18]. Thus, we applied the facial expression recognition module to estimate the human emotions. The observed emotions and their intensities are served as the input to the computational emotional model that affect the internal state of mood and emotions. The mood state triggers the empathic response and then the empathic response is expressed through the virtual facial expression simulator.

### A. *PERCEPTION*

Conventionally there are several studies to extract the facial features [19], [20]. In this study in order to generate the artificial emotions in robot from human facial expressions, we improved the facial expression recognition algorithms [21] based on Constrained Local Model (CLM) with LeaderP clustering algorithms [22] and topological Gaussian Adaptive Resonance theory algorithm (TGART) [23]. Thanks to the clustering algorithms, the system can extract human facial feature points with higher accuracy than fundamental CLM based recognition in real time. Here, we briefly explain the facial expression recognition framework. The task of tracking process is divided into two sequences depending on the number of key frames. Key frames are defined as the number of initial frames to keep patch images and shapes for building x initial cluster during tracking. In the first sequence for CLM, face detection, initial shape formation, parameters calculation, model fitting and optimization process are carried out to define the neutral face shape, and to keep patches and shapes until defined number of key frames. As the prerequisite, patch model and shape model are constructed. The patch model consists of local patch images such as. Eyebrow corner, eye corner, nose bottom, mouth corner etc.

On the other hand, the shape model represents shape variations. Static or dynamic face is captured to detect a face applying Viola-Jones cascade classified [24] from each face frame. Initial shape formulation, local and global parameters are calculated by learned reference shape, mean shape, eigenvector, and eigenvalues during CLM building. In addition, Point Distribution Model (PDM) is applied to generate the 2D feature point positions of each patch image. Here, we utilize CLM based face tracker [25] for automatic facial feature point initialization, accurate model fitting and optimization. At the end of this sequence, the shape of neutral face is stored and will be utilized for calculating the measurement vector. The measurement vector is defined as the set of displacements of facial feature point positions, using Euclidean metric for frame wise facial expression recognition. At the same time, frame wise patches and shapes are accumulated to build the initial clusters. In the second sequence, after defining the natural face shape and initial cluster elements. Two incremental clustering algorithms are considered to build and update clusters dynamically. LeaderP clustering algorithm [22] is applied to build an appearance model. The similar patches will be made closer together to form clusters by appearance model. Clusters can be defined by their median and variance. These clusters will represent the appearance of the facial features. Cluster representative will be formed using Zero-mean Normalized Cross-Correlation (ZNCC) method [26]. Clusters are updated incrementally; assign a weight that will be increased during recurrent update. If the new patch is not belonging to existing clusters, a new patch will be regarded as a new cluster. Furthermore, TGART [23] is applied to build a structure model. The similar shapes will be made closer together to form clusters in the point distribution space by structure model. The similar shapes will be made closer together to form clusters in the point distribution space by structure model.

Clusters with highest activation value for the current shape will be updated if it satisfies the vigilance criterion. Activation value provides likelihood that an input pattern is a probable candidate for being a new cluster or an element of existing cluster. Vigilance is a measurement of similarity between the current shape and the existing cluster's mean relative to tis standard deviation. In this way, structure model will continue to grow incrementally by incorporating new shapes. If there is no cluster that is satisfied criterion of activation value and vigilance, a new cluster will be formed with only one member. Correct positions of patch images will update the structure model and the appearance model. After calculating the final patch positions in structure model, a measurement vector is built by subtracting feature point positions of the current shape with neutral face shape. According to experimental results in reference [21], this face tracking framework has sufficient ability to recognize 6 basic facial expressions such as neutral, surprise, sadness, fear, angry and happy based on Ekman's emotional model [27], [28].

### B. *EMPATHIC APPRAISAL*

#### *1) Computational Emotion Model*

In general, human emotional states are generated by not only facial expressions but also several stimuli from the environment. In addition, researches in the human psychology field have been expected that the human emotional function is composition result of core affect, emotion and mood states [29], [30]. This emotional model is composed of the user's emotional state recognizer and the

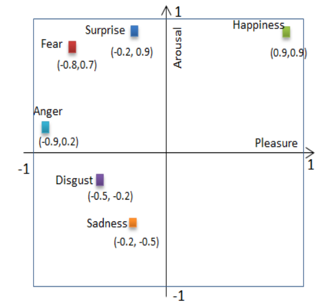


Fig. 2: Position of emotional factors on pleasant-arousal plane [34]

mood state generator, and utilizes (1) and (2) to generate the computational emotion states from the human facial expression information. In this paper, we also utilize the five factors model of personality with a 2D scaling model to avoid the model complexity. However, the consciousness factor is not included. Mehrabian utilized the five factors of personality to represent the emotional information as Pleasure-Arousal-Dominance (PAD) temperament model [31]. The relationship between the five factors of personality and PAD model is derived through the linear regression analysis [32]. This result is summarized as three equations of temperament, which includes pleasure, arousal, and dominance as followings:

$$P_{\alpha} = 0.21E + 0.59A + 0.19N \tag{1}$$

$$P_{\beta} = 0.15O + 0.3A - 0.57N \tag{2}$$

$$P_{\gamma} = 0.25O + 0.17C + 0.6E - 0.32A \tag{3}$$

where, $P_{\alpha}$, $P_{\beta}$ and $P\gamma$ represent the value for pleasant axis ($\alpha$-axis), arousal axis ($\beta$-axis) and dominance axis ($\gamma$-axis), respectively. $O$, $C$, $E$, $A$, and $N$ (where $O,C,E,A,N \in [-1, 1]$) represent the five factors of personality as openness, conscientiousness, extraversion, agreeableness and neuroticism, respectively. Han et al. [33] employed five factors of personality to a 2D (pleasure-arousal) scaling model that is introduced by Russell [34] to represent a computational emotion model (Fig. 1). In this paper, we utilize six basic emotions (Happy, Sadness, Angry, Fear, Disgust, and Surprise). Therefore, $\mathrm{I}_{(t)}^{CA}$ will be written as a following;

$$I_{(t)}^{(CA)} = \begin{bmatrix} ca^{H} \\ ca^{S} \\ ca^{A} \\ ca^{F} \\ ca^{D} \\ ca^{Sur} \end{bmatrix} = \begin{bmatrix} intensity\ of\ happiness \\ itensity\ of\ Sadness \\ intensity\ of\ Anger \\ intensity\ of\ Fear \\ intensity\ of\ Disgust \\ intensity\ of\ Surprise \end{bmatrix} \tag{4}$$

$$\mathrm{ca} \in [0, 1]$$

Han et al. [33] proposed the interactive computational emotion variables ($\Delta\alpha$, $\Delta\beta$), which represent the reaction from current emotional intensities on the pleasant arousal plane. These variables are based on neutral intensity, happiness intensity, anger intensity and sadness intensity. We extend their four emotional factor model to six emotional factors model as core affect-emotion transfer coefficients, such that;

$$\Delta\alpha_t^{CA} = 0.9ca^H - 0.2ca^S - 0.9ca^A \\ -0.8ca^F - 0.5ca^D - 0.2ca^{Sur} \quad (5)$$

$$\Delta\beta_t^{CA} = 0.9ca^H - 0.5ca^S + 0.2ca^A \\ +0.9ca^F - 0.2ca^D + 0.2ca^{Sur} \quad (6)$$

Here, variable $\Delta\alpha$ and $\Delta\beta$ represent the value for pleasant axis ($\alpha$-axis) and activation axis ($\beta$-axis), respectively. In addition, coefficient of each emotion's intensity is determined by Fig. 2. The state of emotion $I_{(t)}^E$ is calculated as a following;

$$I_{(t)}^E = \tanh\left[\gamma^M \left(I_{(t-a)}^E + (P_\alpha.\Delta\alpha_{(t-a)}^{CA}, P_\beta.\Delta\beta_{(t-a)}^{CA})\right)\right] \quad (7)$$

where, $\gamma^M$ ($0 < \gamma^M < 1.0$) is the suppression rate from mood state. It depends on the empathic response combination of current mood state and core affect, the value of $\gamma^M$ will be changed. $\alpha$ takes an arbitrary value as a time delay. $P\alpha$ and $P\beta$ are defined as (1) and (2). Equation (7) calculates the emotion on pleasure arousal plane. We use fuzzy logic in order to calculate the intensity of each emotion that is presented next sub section. In general, mood state will be taken positive or negative state [35]. We assume that it can be represented on pleasant axis in Fig. 2. Therefore, emotion-mood transfer coefficient $\Delta\alpha_t^E$ is defined as a following:

$$\Delta\alpha_t^E = I_t^{E(\alpha-axis)} \quad (8)$$

Finally, mood state is determined as a following:

$$I_{(t)}^M = \tanh\left[\gamma^M \left(I_{(t-a)}^M + \left(P_\alpha.\Delta\alpha_{(t-a)}^E\right)\right)\right] \quad (9)$$

where, $\gamma^M$ ($0 < \gamma^M < 1.0$) is the suppression rate from mood state. $\alpha$ takes an arbitrary value as a time delay. $P\alpha$ is defined as (1). The empathic response, explained in a later part, is the key factor controlling the suppression rate of the mood state. Equation (7) calculates the positions of emotion on pleasure-arousal plane. We apply fuzzy logic to calculate the intensity of each emotion from the position based on the criteria as Fig. 2. The position of each emotion on pleasure and arousal are regarded as input of the fuzzy system to calculate the intensities of each emotion. The membership functions of each emotion are defined as Fig. 3. The definitions of each membership function are tuned in accordance with the criteria positions of each emotion as shown in Fig. 2. Finally, for the process of defuzzification, centroid method is used, which finds a point indicating the center of gravity (COG) of any fuzzy set on a specific interval.

#### *2) Empathic Response*

Davis [9] distinguished two different kinds of empathic responses, i.e., parallel and reactive. Parallel empathic response consists of similar emotions as they are perceived in other person. Whereas, the reactive empathic response does not have to be necessarily similar to the perceived emotional state of other and it is more focused on alleviating the other person's emotional state. The combination of parallel and reactive empathic responses is identified as positive and helpful towards improving the emotional state of other person from negative emotions to positive [36].

The proposed model is designed to exhibit both types of empathic (parallel and reactive) responses. The mood state and emotions of the robot are triggered via external stimuli, which are the emotion intensities from human facial expressions. Therefore, it can be assumed that the mood state of the robot is the reflection of the human emotional state. The empathic response is affected by the factors like personality and mood [16]. In this paper, the personality factors remain static during interaction and has a direct impact over the mood. For this reason, the mood is used as the deciding factor to switch between parallel and reactive empathic responses. The parallel emotions are helpful towards maintaining the other person's current emotional state [36]. Hence, when the mood is positive, the parallel empathic response is triggered. On the other hand, when the mood is negative the reactive empathic response (sympathy) is triggered, focusing on improving one's own distress [11]. The negative mood reflects that the other person is in distress with feeling of negative emotions. Besides, the sympathy is associated with self-efficacy and self-regulation of emotions towards reducing the distress. Thus, in proposed model, the reactive response triggers the high value for the suppression rate for mood state as shown in (10).

$$\gamma^M = \begin{cases} 0.9 & if \quad I_{(t)}^M < 0 \\ 0.6 & else \end{cases} \quad (10)$$

### C. *EMPATHIC EXPRESSION*

For the empathic interaction, it is important to communicate the empathic responses instead of inhibiting [37]. Facial expressions provide an effective channel to communicate emotions [18]. Thus, the empathic response is communicated through the facial expression simulator called Grimace [17]. The Grimace is capable of showing six basic different emotions with varying intensity from low to high using facial expressions. Grimace can also show the combination of two or more expressions at a single instance of time. In this paper, the Grimace shows its facial expressions based on the empathic response. In case of parallel response, the perceived emotions of the user with its intensity are mapped on Grimace. However, when the reactive empathic response is triggered, the robot's internal emotion is carried out to Grimace for the empathic expression. The basic facial expressions are shown in Fig. 4.

## III. EXPERIMENT

An experiment based on short-term interaction was conducted in order to demonstrate the output of the proposed model. The results of two different personalities affecting mood state, emotions, and empathic response are also shown in following sub-section.

### A. ***Experimental Setup***

Through the experiment, the input of facial image data of the user is provided using a webcam, and the output from the facial expression recognition framework is regarded as core affects in computational emotion model.

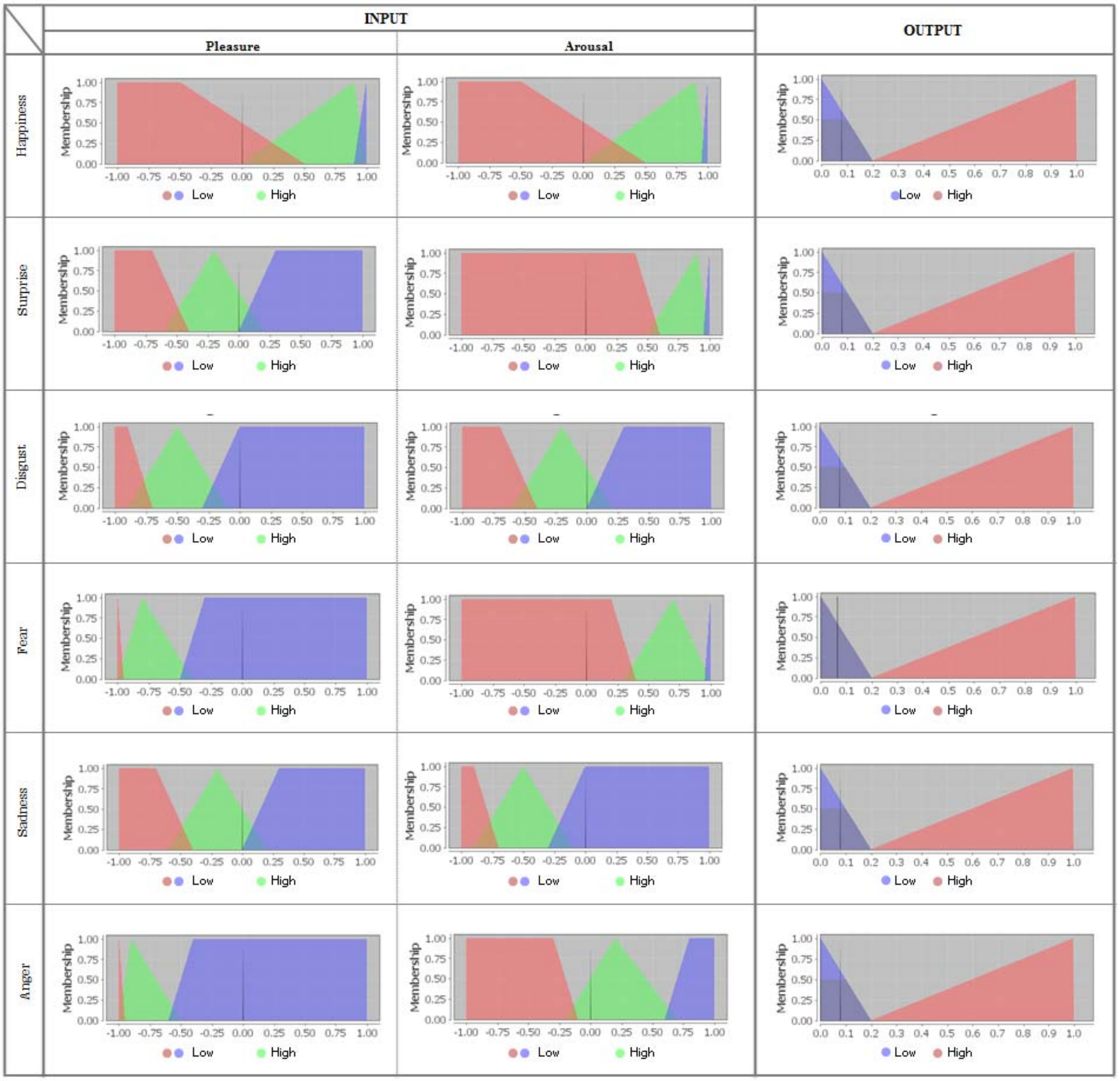


Fig. 3: Definition of membership functions for inputs and output of fuzzy system

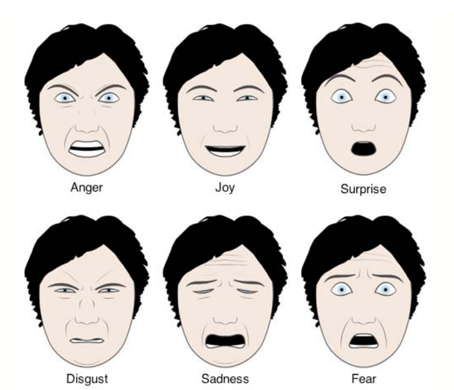


Fig. 4: Six basic emotions expressed by Grimace [17]

TABLE II: Types of Personality

| **Factors** | **Type 1** | **Type 2** |
|---|---:|---:|
| Openness | 0.90 | 0.40 |
| Extraversion | 0.70 | 0.30 |
| Agreeableness | 0.50 | 0.30 |
| Neuroticism | -0.60 | -0.20 |

Furthermore, in order to perceive the difference of personality effect over the empathic response, we utilized the same input data with two different personality types as stated in Table II. However, because the computational emotional model is defined on 2D (pleasant-arousal) scaling model, the four personality factors except Consciousness are applied in the model.

### B. *Results*

From the input of facial image data of the user, the intensity of each emotion is calculated as in Fig. 5. In Fig. 5, the positions at certain time steps, i.e., (a), (b) and (c), are in correspondence with the positions (a), (b) and (c) in Figs. 6 and 7. In response to the core affects as shown in Fig. 5, the emotions are generated on the 2D plane with two different personality types as shown in Fig. 6. As mentioned above, the personality type 1 is more open person. Thus, the effect of core affect is higher than the person with personality type 2. Therefore, the generated emotion in Fig. 6(i) is more approaching to the criteria of emotions than Fig. 6(ii). In Fig. 7, the intensity of each generated emotion is presented which is calculated through fuzzy logic. Due to the difference of personality types, as mentioned earlier, the intensities of emotions are different between Figs. 7(i) and 7(ii). Especially, in Fig. 7(i), around ranges of steps 1 to 30 and 40 to 80, the intensities of sadness and surprise are activated, respectively. In addition, we displayed the Grimace facial expressions corresponding to the intensity of emotions at certain steps. It is clear that the Grimace faces of G1 and G3 show the corresponding emotions, unlike Fig. 7(ii). The intensity of mood is generated from the position on the pleasure axis of 2D plane defined as (8) and (9). Here, Fig. 8 shows the intensity of mood. In Fig. 7 the intensity of happy has positive effect on mood. In addition, the position (b) shows almost same value regardless of personality types. However, the intensities of mood in Figs. 8(i) and 8(ii) are quite different, because of personality factors. From the results of Figs. 6, 7 and 8, it can be considered that the person with personality type 1 denotes an open and an expressive person. In contrast, the personality type 2 represents a calm and quiet person.

In the proposed model, as mentioned in section II, the negative mood state triggers the reactive empathic response and the positive mood state activates the parallel empathic response. Fig. 9 shows the empathic responses which are triggered by mood state. Here, when the empathic response is activated, the output signal shows "1". In contrast, output signal "0" indicates that the empathic response is inactive. In addition, the region (A) and the region (B) represent the parallel and reactive empathic responses, respectively. Incidentally, the fluctuations between reactive and parallel empathic response around step 90-100 is because of the vibrations generated by the mood state. Based on activated empathic response in Fig. 9, the intensity of the emotions from user's facial expressions in Fig. 5 and from computational emotion model in Fig. 7 are selected as the input to the Grimace simulator for the empathic expression. In Fig. 10, the regions (A) and (B) are corresponding to the regions (A) and (B) in Fig. 9, and the regions (A) and (B) represent parallel and reactive empathic response,

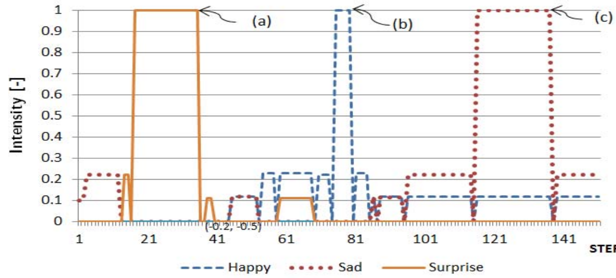


Fig. 5: History of human facial expressions as core affects

respectively. As we can see in Fig. 9, the parallel empathic response is activated at the region (A). Hence, the intensity of emotions from the user's facial expressions is expressed at the region (A) in Fig. 10. In contrast, the intensity of generated emotions is selected as the reactive response at the region (B). Therefore, the resultant intensity of emotions in Fig. 10 is rather different from Fig. 7. As a result, the significant difference of Grimace faces such as G5 and G6 can be seen in Figs. 7 and 10; this empathic response is also in confirmation to the Davis [9] that the reactive empathic response would be different from the perceived emotion in the user.

## IV. Conclusion

This paper proposed an empathic model for human-robot interaction with two different empathic responses exploiting the key factors of social interaction, i.e., personality and mood. It involves mainly three stages, which are: 1) Perception: this refers to the recognition of emotions of the user through facial expression recognition framework. 2) Empathic appraisal: In this stage first the internal the mood and emotions are generated. Since the emotions are generated using 2D plane. The intensity of emotions is calculated through fuzzy logic. Depending on the mood and personality factor certain empathic response is stimulated and the empathic emotion is finalized in accordance with the stimulated empathic response. 3) Empathic expression: this stage deals with the display of the empathic emotion through virtual facial expression simulator. Finally, we conducted the preliminary experiment to observe the behavior of the proposed model. The results of the experiment demonstrated the generation of empathic emotions in continuous manner based on certain empathic response with the difference of personality types. Therefore, due the empathic emotions, there is a possibility to improve the communication ability of robots.

As a future work, we plan to advance the proposed model by incorporating different modulation factors such as: familiarity and liking and to use a physical robot that is able to show the multi-model interaction based on the resultant empathic emotion. With the physical existence of the robot, we can further evaluate the impact of the proposed model in real-time human-robot interaction.

## ACKNOWLEDGMENT

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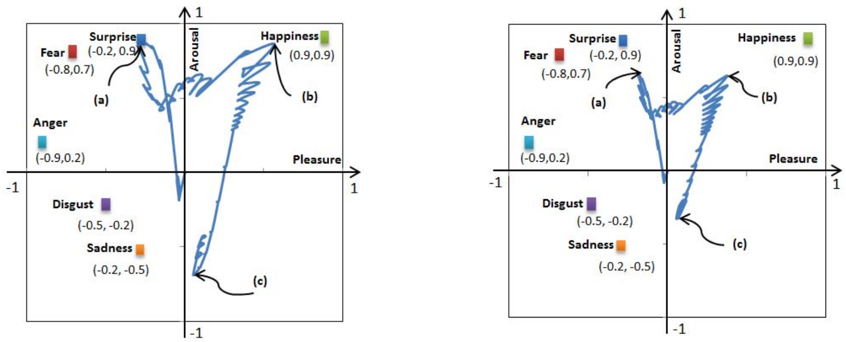
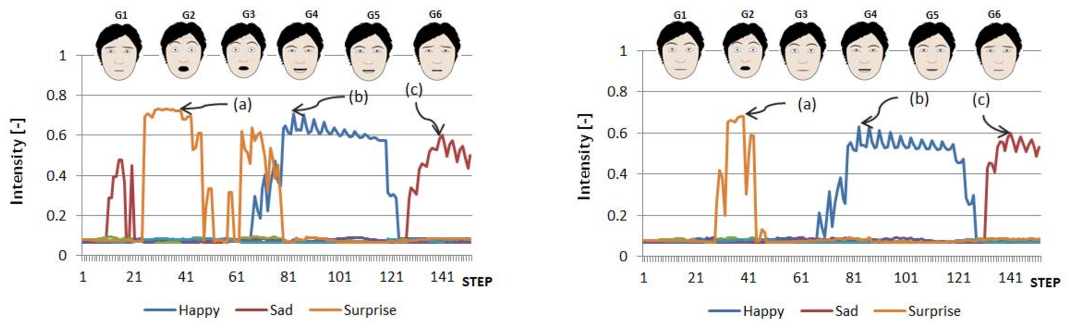


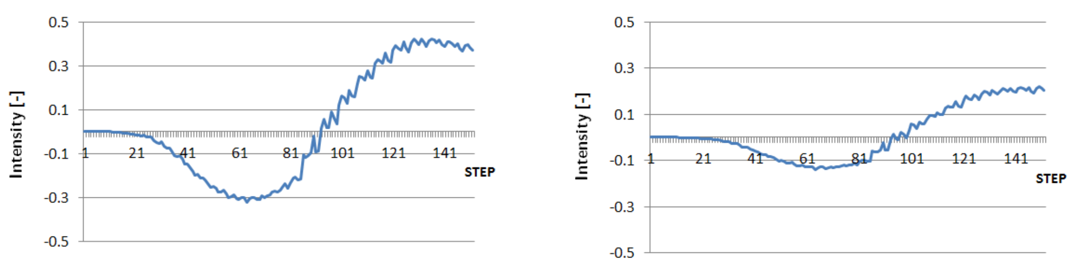

(i) Type 1 Personality (ii) Type 2 Personality

Fig. 6: Generated emotions mapped on 2D plane for two different personality types



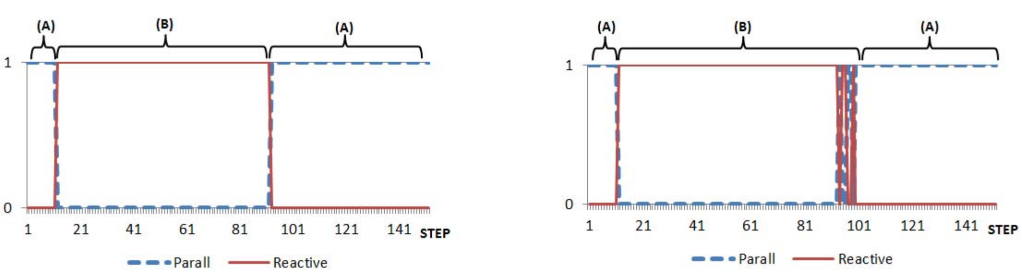

(i) Type 1 Personality (ii) Type 2 Personality

Fig. 7: Intensity of generated emotions in result of 2D plane model




(i) Type 1 Personality (ii) Type 2 Personality

Fig. 8: Output of the mood state in two different personality types




(i) Type 1 Personality (ii) Type 2 Personality

Fig. 9: Activation of empathic response with two personality types

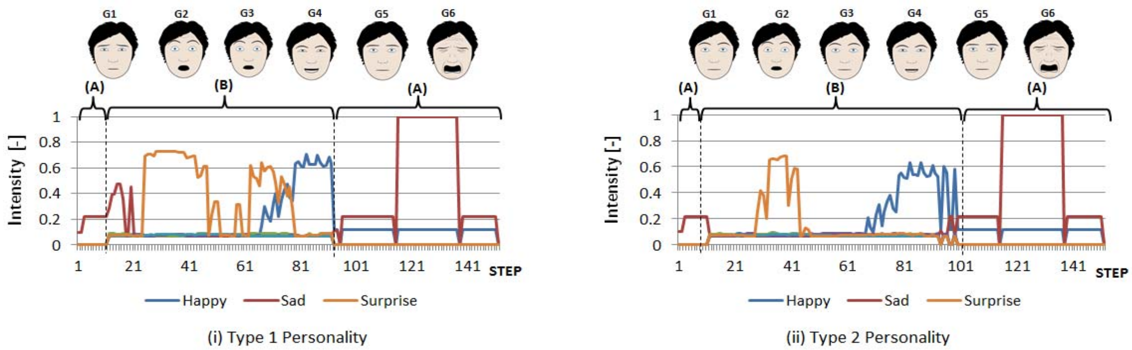



Fig. 10: Emotion intensities based on Parallel & Reactive empathic responses

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