Personal Preference Analysis for Emotional Behavior Response of Autonomous Robot in Interactive Emotion Communication

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<th>メタデータ</th>
<th>言語: eng</th>
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<tr>
<td>出版者:</td>
<td></td>
</tr>
<tr>
<td>公開日: 2011-01-28</td>
<td></td>
</tr>
<tr>
<td>キーワード (Ja):</td>
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<td>キーワード (En):</td>
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<tr>
<td>作成者: TAKI, Ryohei, MAEDA, Yoichiro, TAKAHASHI, Yasutake</td>
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<td>URL</td>
<td><a href="http://hdl.handle.net/10098/2984">http://hdl.handle.net/10098/2984</a></td>
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Robots must understand human intention flexibly before the two can live together, for example. Interaction Emotion Communication (IEC), bidirectional communication based on emotional behavior between human beings and robots, raises the personal affinity a robot has for human beings. IEC consists of three processes – (1) recognizing human emotion, (2) generating robot emotion, and (3) expressing robot emotion. We focus here on generating robot emotion. Emotional behavior patterns desirable in a robot vary with the person, so we also conducted individual preference analysis of emotional behavior.

Keywords: emotion, communication, autonomous robot, fuzzy inference

1. Introduction

Despite increasing opportunities for contact between robots and human beings [1, 2], the technology for realizing interactive communication between the two remains surprising undeveloped, as does the flexible understanding of mutually emotion and intention required for them to live together and communicate smoothly. Some research into understanding human intent and expressing robot intent has used nonverbal information [3–7]. Nonverbal communication includes over 90% of the information concerning the emotion of the interlocutor [8]. Nonverbal communication may be by eye, voice, facial expression, or gesture. Robot facial expression like human beings gives us an uncanny feeling [9].

We have been studying nonverbal robot and human communication. We propose inferring emotion from human behavior [10], in Section 3, starting by extracting a subject’s body features based on Laban’s theory [11]. Using these extracted human body movement, we obtain the basic emotional degree through fuzzy inference [10]. We then evaluated the emotional value of human movement based on Russell’s circumplex model [12].

Our research objective is to realize Interactive Emotion Communication (IEC) – emotion-based bidirectional human and robot communication. We aim to give high interpersonal affinity of robot to human. Moreover, we report on the impression of communication between a human and a robot. We would like to analyze the tendency of desirable robot reaction for emotional behavior through IEC. The aim of this research to inspect the individual preference analysis for robot emotional behavior.

2. Interactive Emotion Communication (IEC)

Our research assumes a bidirectional emotional communication model – Interactive Emotion Communication (IEC) – between human beings and robots as an example of nonverbal communication. Here, emotion refers to movement, e.g., gesture or dance [13] representing emotion directed toward a counterpart.

Assume human being A and robot B in an interaction in which A expresses an emotion to B through gestures. Upon recognizing A’s emotion visually, B expresses an emotion to A. Recognizing IEC requires three IEC processes:

1. (1) recognizing human emotion,
2. (2) generating robot emotion,
3. (3) expressing robot emotion.

Because it remains difficult for robots – although easy for human beings – to communicate through language, we considered communication through emotions. Emotional robot behavior is decided based on an analysis of personal preference analysis, as detailed in Section 4 and shown in Fig. 1. Our eventual goal is to build robots able to recognize human emotion and express their own emotion by bidirectional communication based on an IEC model with high interpersonal affinity.
3. Fuzzy Emotion Inference in IEC

We explain the first step of IEC human emotion recognition used fuzzy inference to determine emotion from body features. We used Laban’s theory and Russell’s circumplex model to decrease fuzzy inference input and output and to simplify fuzzy rules.

3.3. Fuzzy Emotion Inference

Figure 2 shows the Fuzzy Emotion Inference System (FEIS) flow we have proposed, which uses the following algorithm:

1. measuring human emotion using a CCD camera,
2. extracting body features from movement analyzed based on Laban’s theory,
3. calculating the basic emotional degree using fuzzy inference based on body features,
4. obtaining an emotion value using Russell’s circumplex model based on the basic emotional degree,
5. expressing robot emotion based on the emotion value.

This research focuses on four basic emotions – joy (JOY), anger (ANG), sadness (SAD), and relaxation (REL) – in discussing human and robot emotions.

3.2. Laban’s Theory


Laban theorized a bipolar system expressing movement based on fighting form – active, vivid movement – and indulging form – slow, gentle movement. These two forms are the core of effort-shape description.

Effort effectively classifies movement based on Kansei information. Shape shows overall static movement, including shape, which does not consider local movement.
Human emotion is inferred from \( R_x \) (pleasure/unpleasure) and \( R_y \) (arousal/sleep) from FEIS. Human emotion is decided based on where the inference result \(( R_x/R_y )\) is. Emotion value \( E_i : i = \text{JOY}, \text{ANG}, \text{SAD}, \text{REL} \) means emotional strength. \( E_i \) is calculated as follows:

\[
E_i = \sqrt{R_x^2 + R_y^2} \left| \sin(\pi - 2\theta) \right| \quad \ldots \ldots \quad (1)
\]

\[
\theta = \arctan \frac{R_y}{R_x} \quad \ldots \ldots \quad (2)
\]

\[
i = \begin{cases} 
\text{JOY} & 0 \leq \theta < \frac{\pi}{4} \\
\text{ANG} & \frac{\pi}{2} \leq \theta < \frac{3\pi}{4} \\
\text{SAD} & \pi \leq \theta < \frac{5\pi}{4} \\
\text{REL} & \frac{3\pi}{2} \leq \theta < 2\pi
\end{cases}
\]

4. IEC Experiments

In inferring human emotions based on FEIS, we conducted interactive experiments between human subjects and a pet-type robot, defining human emotions as JOY-H, ANG-H, SAD-H, and REL-H, robot emotions as JOY-R, ANG-R, SAD-R, and REL-R, and emotion inferred from human emotional behavior by FEIS as JOY-F, ANG-F, SAD-F, and REL-F.

4.1. Experimental Setup

The pet-type robot was the dog-like AIBO (SONY ERS-7), chosen for its “high interpersonal affinity.” The AIBO program is read and written via personal computer using an exclusive memory stick. Joints have 20 degrees of freedom (DOF).

The experimental environment is shown in Fig. 5 using the example JOY-H. Table 2 shows membership function (see Fig. 3). Subjects expressed different behavior and filled out questionnaires determining membership functions and singleton values.

FEIS was constructed on a computer to collect image data – 3 to 5 frames/s – on human expression. FEIS output is sent to the robot through via a wireless LAN. We also appointed an observer to evaluate FEIS accuracy.

4.2. Preconditions

This experiment was cooperated with two subjects – two university students of 20 generations. Subjects attached five markers – head, both hands, and both feet so that computer extracts body features, and each color was different – red, yellow, green, blue, and pink. We made subjects perform emotional behavior freely without restrictions of expression. Subject expresses his emotional behavior while he images various situation as shown in Table 3. In order to realize a kind of natural situation, we question two subjects about when they easily imaged each

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**Table 2. Membership functions and singleton values.**

<table>
<thead>
<tr>
<th>( L_a )</th>
<th>( L_p )</th>
<th>( L_s )</th>
<th>( L_h )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( s_1 = 150 )</td>
<td>( p_1 = 85 )</td>
<td>( v_1 = 5 )</td>
<td>( b_1 = 20 )</td>
</tr>
<tr>
<td>( s_2 = 300 )</td>
<td>( p_2 = 170 )</td>
<td>( v_2 = 10 )</td>
<td>( b_2 = 45 )</td>
</tr>
<tr>
<td>( s_3 = 450 )</td>
<td>( p_3 = 200 )</td>
<td>( v_3 = 25 )</td>
<td>( b_3 = 90 )</td>
</tr>
<tr>
<td>( s_4 = 700 )</td>
<td>( p_4 = 300 )</td>
<td>( v_4 = 150 )</td>
<td>( b_4 = 200 )</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>( R_x )</th>
<th>( R_y )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( p_{i_1} = 100 )</td>
<td>( m_{i_1} = -100 )</td>
</tr>
<tr>
<td>( p_{i_2} = 200 )</td>
<td>( m_{i_2} = -200 )</td>
</tr>
<tr>
<td>( p_{i_3} = 300 )</td>
<td>( m_{i_3} = -300 )</td>
</tr>
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</table>

**Table 3. Emotional situations imaged by two subjects.**

<table>
<thead>
<tr>
<th>Subjects</th>
<th>Emotions</th>
<th>Situations</th>
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<tbody>
<tr>
<td>A</td>
<td>JOY-H</td>
<td>Trial thing was successful.</td>
</tr>
<tr>
<td></td>
<td>ANG-H</td>
<td>Trial thing was unsuccessful.</td>
</tr>
<tr>
<td></td>
<td>SAD-H</td>
<td>Precious item was broken.</td>
</tr>
<tr>
<td></td>
<td>REL-H</td>
<td>He takes some hot drink.</td>
</tr>
<tr>
<td></td>
<td>JOY-H</td>
<td>His desire was satisfied.</td>
</tr>
<tr>
<td></td>
<td>ANG-H</td>
<td>He felt insulted.</td>
</tr>
<tr>
<td></td>
<td>SAD-H</td>
<td>He was betrayed.</td>
</tr>
<tr>
<td></td>
<td>REL-H</td>
<td>He absorbed himself in hobby.</td>
</tr>
</tbody>
</table>
emotion. Table 3 shows the emotional situations imaged by two subjects.

Emotions of subjects were measured using a camera connected to a personal computer (see Fig. 5). Human emotion was recognized by FEIS. The observer checked FEIS output in real time. FEIS output was sent to the robot through a wireless LAN, and the robot expressed emotion based on FEIS output.

Robot emotion was limited to 4 patterns – JOY-R, ANG-R, SAD-R, and REL-R expressed in 3-6 seconds. Subjects observed the robot in front of him as well and filled out questionnaires on robot emotion based on the patterns above.

Experiments were as follows:

Step 1: The subject extracts a situation in which emotion is easily expressed.

Step 2: The subject expresses emotional behavior based on the 5 color markers worn.

Step 3: The camera images the subject’s emotional behavior recognized by FEIS.

Step 4: The computer sends the human emotion to the robot expressed emotional behavior based on FEIS output.

Step 5: The robot expresses emotional behavior for all human emotion combinations.

Step 6: The subject observes the robot while expressing emotional behavior.

Step 7: Experiment steps 2-4 are repeated within 40 seconds.

Step 8: Questionnaires on subjects’ impressions of robot emotional behavior were checked after experiments.

Experiments used the 16 pattern shown in Fig. 6. The robot expressed emotional behavior based on FEIS output. To simplify experiments, we assumed the following emotional robot expressions:

JOY-R: The robot raises both hands.

ANG-R: The robot drops both hands to the ground.

SAD-R: The robot hangs its head.

REL-R: The robot stretches its legs.

Subjects were informed in advance of what each robot action mean to.

4.3. Robot Emotion Impression

To evaluate all combinations of robot and human behavior, we used 6 adjetival pairs – animal-like–mechanical (S1), interesting–boring (S2), complex–simple (S3), familiar–unfamiliar (S4), natural–unnatural (S5), and likable–dislikable (S6). Subjects evaluated robot reactions using 7 scores (−3 to 3). Adjetival pairs were selected as Kansei word referring to past references [17, 18].

We defined evaluation value $\sigma$ to detect the likability degree of subjects. $\sigma$, which is the weighted sum of subject’s evaluation score $S_i$ (i = 1, …, 6) in questionnaire, is calculated as shown in Eq. (3).

$$\sigma = \sum_{i=1}^{6} \alpha_i S_i$$  \hspace{1cm} (3)

We asked both subjects the significance weight $\alpha_i$ (i = 1, …, 6) for 6 adjetival pairs in questionnaire to calculate $\sigma$. In advance, we questioned two subjects about the percentage of significant factor for each adjetival pair. The weights $\alpha_i$ are expressed with the percentage for “Animal-like ($\alpha_1$),” “Interesting ($\alpha_2$),” “Complex ($\alpha_3$),” “Familiar ($\alpha_4$),” “Natural ($\alpha_5$),” and “Likable ($\alpha_6$).”

After experiments, we obtained ($\alpha_1$, $\alpha_2$, $\alpha_3$, $\alpha_4$, $\alpha_5$, $\alpha_6$) = (0.15, 0.05, 0.15, 0.15, 0.0, 0.5) for subject A, (0.15, 0.1, 0.025, 0.1, 0.125, 0.5) for subject B as the weight of score $S_i$. By using these weights, we calculate the evaluation value for questionnaire. Subject A’s and subject B’s evaluation values ($\sigma_A$, $\sigma_B$), which were calculated with Eq. (3), were useful when we make a comparison between the personal preference.

4.4. Experimental Results

Table 4 shows evaluations for subjects A ($\sigma_A$) and B ($\sigma_B$). In this table, $\rho$ means Spearman rank correlation coefficient, detailed later. Fig. 7 shows differences of impressions between the two subjects. With impressions consistent between subjects, we arranged favorable adjectives at left side and unfavorable at right. These impressions were graded with 7 scores for 6 items. The better the impression, the farther left it is (subject A: solid line; subject B: broken line). Results are summarized as follows:

![Fig. 6. 16 experimental patterns.](image)

Table 4. Evaluation of experimental results.

<table>
<thead>
<tr>
<th></th>
<th>JOY-R</th>
<th>ANG-R</th>
<th>SAD-R</th>
<th>REL-R</th>
</tr>
</thead>
<tbody>
<tr>
<td>JOY-H</td>
<td>$\sigma_A$</td>
<td>0.90</td>
<td>0.40</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
<td>$\alpha_B$</td>
<td>1.90</td>
<td>1.90</td>
<td>−1.58</td>
</tr>
<tr>
<td></td>
<td>$\rho$</td>
<td>0.57</td>
<td>0.71</td>
<td>−0.77</td>
</tr>
<tr>
<td>ANG-H</td>
<td>$\sigma_A$</td>
<td>−0.40</td>
<td>0.20</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>$\alpha_B$</td>
<td>−2.05</td>
<td>−1.18</td>
<td>0.48</td>
</tr>
<tr>
<td></td>
<td>$\rho$</td>
<td>0.10</td>
<td>−0.33</td>
<td>−0.62</td>
</tr>
<tr>
<td>SAD-H</td>
<td>$\sigma_A$</td>
<td>0.85</td>
<td>0.25</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
<td>$\alpha_B$</td>
<td>1.90</td>
<td>1.18</td>
<td>1.25</td>
</tr>
<tr>
<td></td>
<td>$\rho$</td>
<td>0.71</td>
<td>−0.15</td>
<td>0.45</td>
</tr>
<tr>
<td>REL-H</td>
<td>$\sigma_A$</td>
<td>−0.25</td>
<td>0.05</td>
<td>0.40</td>
</tr>
<tr>
<td></td>
<td>$\alpha_B$</td>
<td>0.80</td>
<td>1.40</td>
<td>−2.68</td>
</tr>
<tr>
<td></td>
<td>$\rho$</td>
<td>0.25</td>
<td>0.00</td>
<td>−0.58</td>
</tr>
</tbody>
</table>

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JOY-H Subject A evaluated likable–dislikable highly in all combination (JOY-R, ANG-R, SAD-R, and REL-R vs. JOY-H). Subject A did not feel bad impression to robot when he was in joy. Subject B’s preferences are clear, especially in contrast to subject A’s, when they were opposed, as in JOY-H vs. SAD-R.

ANG-H Both subjects had relatively unfavorable impressions of ANG-H. Subject A felt sympathetic but subject B was troubled in case of ANG-H vs. ANG-R. Both were displeased when the robot expressed pleasure – JOY-R and REL-R – after subject expressed ANG-H.

SAD-H Both subjects had a good impression when the robot expressed JOY-R for SAD-H. We think that the robot expressing JOY-R is happy, but both subjects felt encouraged by the robot. Subjects’ evaluations were comparatively similar.

REL-H Subjects A and B clearly had different preferences. Subject A evaluated REL-H vs. REL-R the highest due to feeling sympathy for the robot’s emotion. In contrast, subject B evaluated REL-H vs. ANG-R the highest due to feeling that the robot was sulky and anger although robot actually wanted to be friends.

Figure 8 show FEIS output and movement timing expressing robot emotion for the best combination with high evaluation in Table 4. Fig. 8 graphs show subject B’s high evaluation combination. The X-axis is time for one experiment (40 seconds) and the Y-axis emotion value (Ei). Vertical lines show average FEIS output per second. The robot expressed emotion 3 to 5 times within 40 seconds, and FEIS output JOY-F, ANG-F, SAD-F, and REL-F inference results successfully. Robot JOY-R, ANG-R, SAD-R, and REL-R emotion complied with inference results.

Vertical bold lines show the timing of robot emotion. Robot emotion frequency is important for evaluating human impression. We confirmed that the personal preference was appeared for various robot emotional behavior. In the next step, we should perform the experiment that we investigate tendency of the general personal preference.

4.5. Discussion

Subject impressions confirmed what they feel regarding robot emotion, e.g., they were cheered by JOY-R when they feel sadness. This has very important implications for further development. We calculated Spearman rank correlation coefficient \( \rho \) (Table 4) to inspect these impressions referencing [16]. \( |\rho| \geq 0.6 \) shows strong correlation between two subjects’ impressions. The strongest negative correlation was in JOY-H vs. SAD-R, while the strongest simultaneous positive correlation was JOY-H vs. JOY-R and SAD-H vs. JOY-R. In the case of JOY-H vs. SAD-R, the two subject’s impressions differed markedly. In this case, two subjects’ impressions were reverse plus and minus though same robot’s reaction. Through robot emotional reactions, we confirmed that robot emotion affects to human’s impression.

Results of this experiment confirmed that robot emotion gives different impressions. It is important because
impressions include the variety of human preference. We thus must construct a way to transform robot emotion impression correctly through emotional behavior.

5. Conclusions

We have constructed basic IEC-based communication between human beings and robots, and have analyzed the human impression for the actual robot through emotional behavior. We confirmed that the robot reaction for human emotional behavior gives different impression to subjects. Experimental results suggest guidelines for raising interpersonal affinity between the two. Human beings and robots express emotional behavior in IEC, so we hope that IEC may effectively improve human expression in conditions such as autism and major depression, thereby lowering stress in daily life.

We plan to construct a system in which the robot conducts all processes. Because fuzzy rule parameter tuning takes much time for individual subject adaptation, we must develop a system making fuzzy rules easy to construct even in cases of experiments with involving large numbers of subjects.
References:


Acknowledgements

This research was supported in part by the Ministry of Education, Science, Sports and Culture, Japan, Grants-in-Aid for Scientific Research (C), 2009-2010, 20500203.
Name: Yasutake Takahashi

Affiliation: Department of Human and Artificial Intelligent Systems, Graduate School of Engineering, University of Fukui

Address: 3-9-1 Bunkyo, Fukui 910-8507, Japan

Brief Biographical History:
2000-2009 Assistant Prof., Department of Adaptive Machine Systems, Graduate School of Engineering, Osaka University
2003-2009 Member of Exec. Committee for RoboCup Middle Size League
2006-2007 Visiting Researcher, the Fraunhofer IAIS, Germany
2009- Senior Assistant Prof., Department of Human and Artificial Intelligent Systems, Graduate School of Engineering, University of Fukui

Main Works:

Membership in Academic Societies:
• The Robotics Society of Japan (RSJ)
• Japan Society for Fuzzy Theory and Intelligent Informatics (SOFT)
• The Japanese Society for Artificial Intelligence (JSAI)
• The Institute of Electrical and Electronics Engineers (IEEE)