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Designing Reactive Emotion Generation Model for Interactive Robots

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Abstract— **Design of reactive emotion generation mechanism for interactive robots is proposed in this paper. Sorts of reactive emotions and the framework to generate these emotions against stimuli were identified based on psychological researches on humans' emotions. Computational models of reactive emotion system were also proposed with dynamic models. Each model realized necessary characteristics for reactive process successfully. The developed model was implemented in a toy-like robot which is called 'GOMY'. The robot can show emotional response reactively against stimulus change. The proposed reactive emotion model can be considered as the most basic foundation of general emotional process for interactive robots.**

I. INTRODUCTION

Making a robot responsive to stimuli is the very starting point of building an interactive robot. Emotions are one of universal signals which represents valenced response against external stimuli. Therefore, emotional manifestation against salient stimulus is the key characteristic for an artificial interactive agent to be regarded as a believable one [1]. Especially, it has been proposed that there exists primitive emotions other than highly elaborated emotions which are related with deliberation through cognitive process. Because it has been found that these primitive emotions are more related with reptilian brain structure, it can be assumed that primitive emotions would have more reactive characteristics than others. Therefore, basic reactive mechanism of emotions can be considered as a first step to build emotionally responsive robots.

There have been many researches to design general mechanism of emotions for robots. Kismet is a robot that can understand humans' proto-social signal and express emotions about the stimulus' significance against the robot's drive state. The synthetic nervous system(SNS) of the Kismet is composed of a perception, a drive, an emotion and a behavior system [1]. Emotions were considered to be the basic mean to construct the social relationship in this research. Kismet's emotions could be generated through perception and appraisal processes against external stimuli according to the robot's current drive. The proposed reactive mechanism focuses only on here-and-now emotional response without deliberative appraisal. Primitive emotions is directly coupled with sensory information in accordance with corresponding drive. The primitive emotions were defined as dynamically varying states. Even though the sort of emotions which is handled in the reactive process is fewer than the emotions of Kismet, this research has focused on the establishment of basic mechanism of reactive emotional process in more detail. It was assumed that it would be able to be applied to make toy-like robots more emotionally responsive and interactive with the reactive process. In addition, emotional response against novel stimuli could not be learned in the Kismet's SNS. Learned emotional response can make interactive robots more adaptive and believable in dynamic environment. Therefore, simple learning process of reactive emotion mechanism was considered as an important component in the proposed model.

Learning was also considered as an important process of emotional robots in the research of metal model of WE4-RII robot. The WE-4RII robot and its mental model was developed along with the research which emphasized emotions as a mean to make believable robots [2]. Human-like emotional reactions made the WE-4RII robot look like having vitality, i.e. being believable. The robot's emotions were modeled with second order differential equations, and the characteristics of emotional responses could change according to the parameters of the equations [2]. The operant conditioning process was included for learning in the mental model. The robot could learn the valence against novel stimuli with this process. The robot can learn emotional appraisal of novel stimuli with operant conditioning process. However, temporal relation of stimuli is learned in the proposed model instead of stimuli's appraisal itself. Therefore, learning can take place between any stimuli presented to robots in the proposed model.

The proposed emotion generation mechanism has similar components with previous researches on robot's emotion mechanism. However, the purpose of this research lies mainly on identifying the characteristics of reactive emotions, and building a general framework of reactive emotions for interactive robots. For this purpose, characteristics of reactive emotions have been studied in a top-down manner. Necessary processes to generate reactive emotional response have been identified based on this study. Their computational models of each process were proposed using dynamic models in a bottom-up manner. The emotion generation model was implemented in a toy-like robot, and the robot can show emotional response successfully against stimulus' change.

In the section II, the notion behind reactive emotion mechanism design and the resultant framework will be presented. In the following section, detailed computational

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models of each process will be discussed. In the section IV and V, an interactive robot in which the proposed model was implemented will be introduced and exemplar working of emotional response will be presented.

II. TOP-DOWN DESIGN OF ROBOT'S REACTIVE EMOTIONS

A. Reactive Emotions for Interactive Robots

What kinds of emotion should be expressed in the robot's reactive emotion generation process? Emotions in the reactive level are generated about the characteristics of the stimulus at fast and not related with cognitive functions. According to Ortony et al., 'proto-affect' and 'primitive emotion' are manifested in the reactive and routine level of information processing [3]. The proto-affect is the emotional response based on the assignment of positive and negative valence to stimuli. Discriminating between good and bad stimuli is the very basic mechanism of reactive emotions. Therefore, the delight and distress can be regarded as the basic emotions of the robot's reactive emotion mechanism. Another category of primitive emotion is the emotional reaction about possible future. The future in the routine level is not the explicit expectation by cognitive interpretation but the implicit anticipation by the past experience [3]. The emotions about possible future were characterized as 'Positive feeling about a potential good thing' and 'Negative feeling about a potential bad thing'. The joy and fear could be defined as the corresponding reactive emotions. Accordingly, four emotions, i.e. delight, distress, joy and fear, were selected as the reactive emotions for interactive robots and they are summarized in the Table I.

TABLE I: Selected Reactive Emotions and Their Characteristics Description by Ortony et al.

Emotion	Characteristics
Delight	Positive feeling about good thing
Distress	Negative feeling about bad thing
Joy	Positive feeling about potential good thing
Fear	Negative feeling about potential bad thing

B. Reactive Emotion Generation Framework

Necessary functional components for the reactive emotion generation process can be defined according to the characteristics of the reactive emotions mentioned in the section II-A. At first, determining the valence about any given stimulus is necessary in order to discriminate between the positive and negative emotions. The temporal relation between stimuli should also be able to be learned in order to predict potential good or bad things. Therefore, the valence evaluation and temporal learning of stimuli's relation can be selected as necessary processes for the robot's reactive emotion generation system [4], [3]. There is another necessary feature of the reactive process which can be ascribed not to the characteristics of reactive emotions themselves but to the dynamic change of emotional responsiveness against repeated stimuli. When a specific stimulus is given repeatedly to human, the emotional response against this stimulus may not continue uniformly until the stimulus will be removed. This temporal characteristic of emotional response is manifested by the habituation mechanism in the living organism. It can also make the robot respond emotionally only against salient stimuli. Therefore, the habituation process was also selected as a basic component of the reactive process in a proposed framework.

Figure 1 represents the schematics of the reactive emotion generation where every component is depicted. Habituation process is applied to every stimulus commonly in order to determine the effective salience of the stimuli. The salience of the stimulus decreases along with the repeated presentation of the stimulus through habituation process. The decreased salience reduces the strength of corresponding emotions. When the salience goes below certain level, the corresponding emotions will not occur because of low salience of stimulus. Therefore, habituation process for every stimulus in the figure 1 affects the strength of emotional response. The valence of stimulus is basically evaluated according to the robot's drive state. The way of analyzing the stimulus' valence is determined according to the stimulus' relation with the robot's drive. When a stimulus satisfies a specific drive of the robot, the stimulus is categorized as a satiating stimulus. The satiating stimulus will be evaluated as positive or negative according to the current drive state through the upper pathway in the reactive process framework. It can generate delight and distress emotions resultantly. On the other hand, the robot can also have no preference about the general stimulus when it is not related with robot's any drive. Because there are no standards to evaluate the valence about the stimuli, the general stimuli's valence cannot be evaluated only with stimulus itself. However, if there exists temporal relation between a general stimulus and any satiating stimuli, the general stimulus can be evaluated as a potential good or bad thing because the general stimulus becomes signaling the upcoming satiating stimulus upon previous experience. The temporal relation is learned with the classical conditioning component in the Figure 1, and the valence of general stimulus can be evaluated as positive or negative emotions, i.e. joy and fear, after the relation with any satiating stimuli was learned by the classical conditioning process.

III. COMPUTATIONAL MODEL OF REACTIVE EMOTION GENERATION

A. Elementary Activation Model of Emotional State

The strength of emotions becomes different according to the implications of stimulus. Therefore, the strength of emotional state should be able to be influenced by the importance of the stimulus' implications. The strength of emotions also affects the continuation of the emotional state generally. The emotional state exists longer as the strength of emotions becomes stronger. Moreover, there exists temporal dynamics in emotions. When a stimulus is given, the emotional state arises and decays afterwards with time. In order to model the characteristics of emotional state change, an elementary

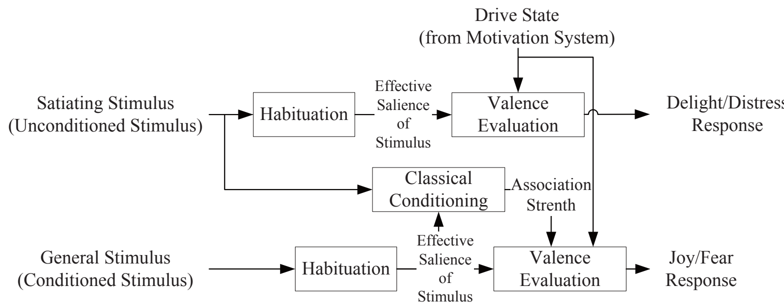

Fig. 1: Schematics of reactive emotion generation process

function of emotions was designed. Aforementioned dynamic characteristics of emotional state change can be realized with exponential functions and the arbitration of the exponential function's output with a sigmoid function.

Elementary function of emotions was designed with exponential functions. The elementary function is composed of a rising section and decaying section:

$$elf(t) = \begin{cases} 0, \\ \qquad \text{if } t < t_0; \\ 1 - e^{-(t-t_0)/\tau_r}, \\ \qquad \text{if } t_0 \le t < t_0 - \tau_r \ln(1-M); \\ e^{-(t-t_0+\tau_r \ln(1-M) - \tau_d \ln M)/\tau_d}, \\ \qquad \text{if } t_0 - \tau_r \ln(1-M) \le t; \end{cases} \quad . \tag{1}$$

where t_0 is the starting time of the emotional response and M which ranges between 0 and 1 is the peak value of the strength of emotional response. τ_r and τ_d are the time constants of exponential responses. The emotional state usually arises at fast, and decays more slowly than the rising time. Therefore, different time constant between rising and decaying section was applied.

The effective strength of an emotional state at a specific time can be calculated as the summation of every elementary function that was previously initiated by effective unit stimuli. And as for the resultant emotional strength of an emotional state, a sigmoid function was applied to the total sum of every elementary function:

$$E_i(t) = sigmoid\left(\sum_j elf_j(t)\right), \tag{2}$$

$$sigmoid(x) = \frac{2}{1+e^{-x/\sigma}} - 1$$

where i represents the index of the specific emotional state. Because the elementary functions are summed linearly, the characteristics of each elementary function are preserved. The non-linear and saturation characteristic of the sigmoid function is also useful to handle extreme values of summed elementary functions. Because sigmoid function's characteristic can be seen in the psychological and physiological changes of humans' emotion-related states, the proposed model of emotional strength seems to be proper to handle emotions' modeling for the robot's more believable emotions [5].

B. Components of Reactive Emotion Generation

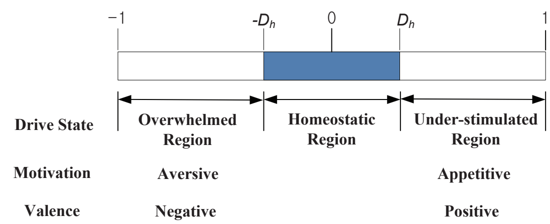

Fig. 2: The relation between drive state, motivation and valence of stimulus

1) Valence Evaluation and Motivation Model: The motivation system is not the part of reactive emotion generation system, but is closely related with valence evaluation of stimuli. The motivation for a drive state is determined according to how the drive has been satiated by the stimulus. The motivation system in this research was implemented based on the Kismet's homeostatic model of a drive process [1] and it is shown in the Figure 2. The drive state always increases when there is no satiating stimulus, and the drive state becomes under-stimulated resultantly. The motivation to demand the satiating stimulus is generated under the under-stimulated drive state, i.e. appetitive motivation, and the satiating stimulus is evaluated as good one. On the other hand, the drive state decreases along the satiating stimulus presentation. The drive state becomes overwhelmed when the satiating stimulus has been given for a long time. Then, the motivation to keep away from the stimulus is generated, i.e. aversive motivation, and the stimulus is evaluated as bad one. If the satiating stimulus has been presented moderately, the drive state will remain in the homeostatic region and the stimulus will not generate specific emotional response. The drive state changes dynamically according to the following equation:

$$\frac{dD_k(t)}{dt} = \Delta_k + \sum_i \Delta_{k,S_i}, \tag{3}$$

where $D_k(t)$ is a robot's drive state which is designated the index k at time t, Δk is the unit change of the k_{th} drive when there is no satiating stimulus for the drive, and Δ_{k,S_i}

is the unit change of the drive state by the present satiating stimulus S_i. When there are multiple stimuli for the drive, all the change by each stimulus are summed and affect the drive change totally. According to the motivation to satisfy any drive state, stimuli's valence is evaluated following the scheme in the Figure 1.

2) Habituation Model: The habituation process can be modeled with reference to dynamic modeling of living organism's habituation process in previous researches. There have been many computational models of simulating neuronal activities of the habituation process precisely [6]. The habituation model that was proposed by Wang & Hsu was applied as the basis for designing habituation process because it models the core adaptation characteristic of habituation in various time domain effectively [7], [8]. The following equation represents the habituation model which was proposed by Wang & Hsu:

$$\begin{aligned} \tau\frac{dy(t)}{dt} &= \alpha m(t)\left[y_0 - y(t)\right] - \beta y(t)S(t) \\ \frac{dm(t)}{dt} &= \gamma m(t)\left[m(t)-1\right]S(t), \end{aligned} \tag{4}$$

where $S(t)$ represents the given stimulus' strength, $y(t)$ represents the neuronal activity by habituation, and $m(t)$ is the variable related with long term memory. Parameters in the equation 4 stand for dynamic characteristics of the habituation process. τ is the time constant of habituation; α regulates the rate of recovery; β controls the effectiveness of the stimulus; and γ controls the time constant of long term effect. The neuronal activity, $y(t)$ decreases toward zero when the stimulus is presented, i.e. $S(t)$ becomes one. $y(t)$ will recover to one when the stimulus is removed. In addition, $m(t)$ changes slowly rather than the variable $y(t)$, and influences the habituation in the long-term.

Even though the Wang & Hsu's model represented well neuronal habituation activities, it had to be modified in order to be applied to the robot's reactive emotion generation process. Because the purpose of reactive emotion generation process modeling is not to model exactly the mechanism behind habituation but to make the reactive emotions' characteristics be adjustable by design, dynamic characteristics of the habituation was distinctively modeled as possible in the proposed model. The following equation represents the modified habituation model:

$$\begin{aligned} \tau_h\frac{dH_i(t)}{dt} &= \alpha_h m_i(t)\left[1 - H_i(t)\right]\left[1 - S_i(t)\right] \\ &\quad -\beta_h\left[1 - m_i(t)\right]H_i(t)S_i(t) \\ \frac{dm_i(t)}{dt} &= \gamma_h m_i(t)\left[m_i(t)-1\right]S_i(t), \end{aligned} \tag{5}$$

where $S_i(t)$ represents the stimulus designated by an index i, $H_i(t)$ is the habituated strength of the stimulus, and $m_i(t)$ represents the effect to the habituation by long-term memory. Every parameter, i.e. τ_h, α_h, β_h, γ_h, also has the same meaning with the parameters, i.e. τ, α, β, γ in the equation 4. In the proposed mode, habituation and recovery are separated by making the stimulus' effect opposite, i.e. multiplying $1 - S_i(t)$ to the recovery term but multiplying $S_i(t)$ to the habituation term. The long-term memory also affects differently. When a stimulus has been learned in long-term, $m_i(t)$ has became closer to zero. Therefore, the stimulus' strength will be habituated faster and recover to the original state slower. However, the stimulus' strength will become weaken slowly and recover to the original strength at fast when the stimulus is very rare in the long-term.

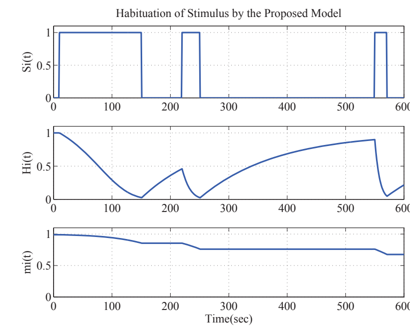

Fig. 3: Habituation by a stimulus pattern during 10 minutes when the stimulus has not been learned in the long term: α_h=0.1, β_h=5, γ_h=0.02, τ_h=10, $m_i(0)$=0.99

Figure 3 represents habituation result of a stimulus during 10 minutes. The stimulus was given for about two minutes at first and the strength of the stimulus becomes habituated by continuing the stimulus presentation. The habituated strength of the second stimulation became much smaller than the first because there is not enough time for recovery between the first and the second stimulation. Then, the third stimulus' habituated strength becomes similar with the first one, because there is enough time for recovery. However, the speed of habituation becomes faster for the third stimulation by the long-term learning, i.e. decrease of the variable $m_i(t)$.

3) Classical Conditioning Model: The temporal learning of the relation between stimulus changes can be implemented using the classical conditioning process. The robot can relate satiating stimuli with any general stimulus that preceded the general stimulus repeatedly through the classical conditioning. When a general stimulus becomes to have strong temporal relation with a specific satiating stimulus, the valence of the general stimulus can be evaluated according to the drive state which requires the satiating stimulus. According to this relation, the satiating stimuli correspond to unconditioned stimuli and the general stimuli correspond to conditioned stimuli in the classical conditioning scheme. A classical conditioning process model (S-D model) which was proposed by Schmajuk and DiCarlo was applied as the basis for the reactive emotion generation process[9], [10]. The modified S-D model could also simulate the basic function of classical conditioning process. The habituation part of the original S-D model was replaced with the proposed habituation model in the section III-B.2 without long-term memory model. The proposed classical conditioning process is defined by the equations:

$$\begin{aligned} \frac{dw_{ij}(t)}{dt} &= \alpha_c\left[1 - |w_{ij}(t)|\right]EO_{ij}(t) \\ EO_{ij}(t) &= \mathrm{sgn}\left(1 - y_i(t) - y_{th}\right)S_i(t) \\ &\quad -\beta_c\left[1 - y_j(t)\right]w_{ij}(t), \\ \frac{dy_j(t)}{dt} &= \alpha_h\left[1 - y_j(t)\right]\left[1 - S_j(t)\right] \\ &\quad -\beta_h y_j(t)S_j(t) \end{aligned} \tag{6}$$

where α_c is the learning rate, β_c is the disassociation rate, and both α_h and β_h are the habituation related parameters mentioned in the equation 5. The associative weight $w_{ij}(t)$ represents the weight between a satiating stimulus(unconditioned stimulus) $S_i(t)$ and a general stimulus(conditioned stimulus) $S_j(t)$. The error in the prediction, $EO_{ij}(t)$ measures the difference between the current general stimulus and the prediction based on learned experience. The weight increases when the satiating stimulus is presented while the previously given general stimulus still takes affect through the habituation process., i.e. $y_i(t)$ still has some value lower than one. Figure 4 shows the weight learning between two stimuli, i.e. unconditioned stimulus(US) and conditioned stimulus(CS). When the CS is presented first and the US follows right after, the weight between two stimuli increases. However, the weight between two stimuli decreases when only one stimulus is given. With the proposed classical conditioning process, reactive emotions can be generated about potential good or bad stimulus.

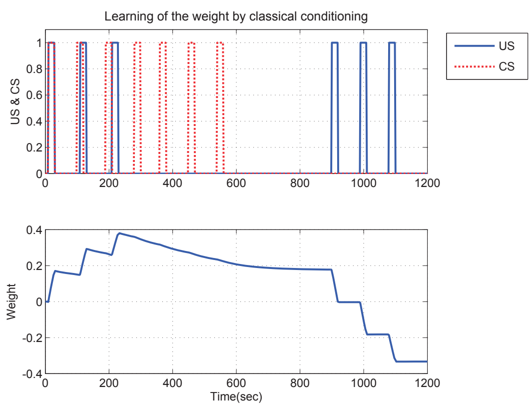

Fig. 4: Learning of the prediction of unconditioned stimulus by conditioned stimulus' presentation: α_c=0.01, β_c=0.3, y_{th}=0.1, α_h=0.1, β_h=5

4) Reactive emotion's strength: The type of reactive emotional reaction is decided according to the process in the Figure 1 using the computational algorithms of valence evaluation, habituation and classical conditioning. The strength of the delight and distress emotions is basically decided according to the strength of the motivation and habituated salience of the stimulus:

$$RE_{delight/distress} = D_k \times H_i. \tag{7}$$

For the joy and fear emotions, the strength of emotion is determined by the associative strength with the stimulus which will satisfy current drive. Therefore, the weight between the current general stimulus and the satiating stimulus in included in the calculation of the emotions' strength:

$$RE_{joy/fear} = D_k \times H_i \times w_{ij}. \tag{8}$$

IV. GOMY: AN INTERACTIVE ROBOT WITH REACTIVE EMOTIONS

An interactive robot, GOMY(intimate pronunciation of a little bear in Korean), was developed in order to embody the developed reactive emotion process. Since baby bear-like doll is one of the characters with friendly appearance, we chose baby bear-like doll as an external shape of the GOMY as shown in the figure 5. There are several ways

Fig. 5: The appearance of GOMY was developed with a commercial bear doll of AURORA co.

to express the robot's emotion such as gesture, voice, facial expression, and so forth. GOMY uses gesture to express its emotion. Figure 6 shows the mechanical structure of GOMY. GOMY has 6 degrees of freedom(DOF): two DOFs for each arm and one DOF for each leg. It can generate up/down, open/close, and rotational motion of each arm. It can also generate up/down motion of each leg, which also enables to incline the body back-and-forth. Each joint is actuated by R/C servo motors (HES-288).

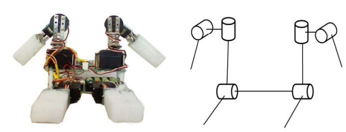

Fig. 6: Mechanical structure of GOMY robot

To recognize humans' touch, GOMY has four FSRs in each arm and leg and two capacitative sensors on its head and belly. FSRs and capacitative sensors detect touching each part of the robot.

V. EMOTIONAL RESPONSE EXPERIMENTS WITH THE GOMY ROBOT

The proposed emotion generation model was implemented in the GOMY robot. In pilot experiments, robot's reactions for each emotion and its strength were predefined. When a certain emotional state arises over predefined threshold level, a corresponding action is expressed. Because only the reactive process was implemented in the robot, robot's behavioral manifestation was simplified in these experiments. Emotional response about touch stimulus was recorded in experiments and the result showed that the emotion system worked in the way of target characteristics of reactive emotions. The third graph in the figure 7 shows the change from positive emotion to negative emotion by drive state and the decrease of emotional strength along with repetitive stimulus. In this experiment, it was assumed that the robot had a need for gentle touch of its belly. Therefore, when stimulus touching the robot's belly was given repeatedly, the drive state needs touching decreased along with every touching and it is shown on the second graph of the figure 7. The robot showed delight in the beginning because the robot had appetitive motivation for belly touch stimulus. The emotional response changed to distress after the robot became to have aversive

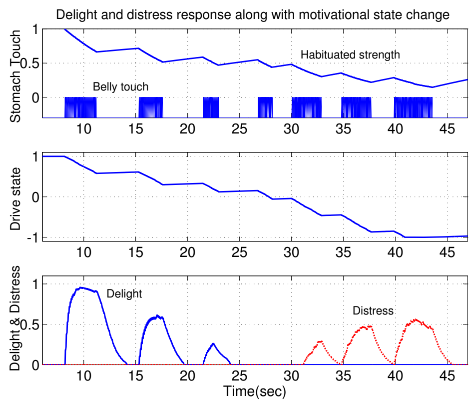

Fig. 7: Delight and distress response about repetitive satiating stimulus

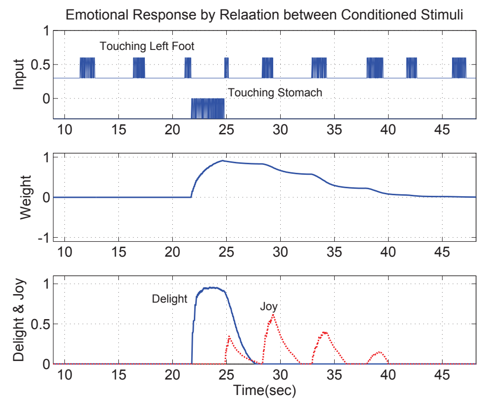

Fig. 8: Joy response about conditioned stimulus with satiating stimulus

motivation for too many touching. This result showed the basic valenced reaction according to motivational change by stimulus experience.

The change of emotional strength by habituation also could be identified in this result. When the same stimulus was presented repeatedly, the saliency of the stimulus decreased by habituation process and it is shown on the first graph of the figure 7. Along with the change of emotional strength, the robot could show different behavioral response against the same stimulus.

Touching the GOMY's foot was set as being not related with any drive in the second experiment. In the beginning, touching foot did not generate any emotional response because the stimulus was not related with satisfying any drive. When the robot's belly was touched right after the robot's foot was touched, these two stimuli's temporal relation learned. As a result, joy response was generated when the foot was touched again after learning. The learning result was represented with the increased weight between them in the classical conditioning process on the second graph of the figure 8. The learning rate was set high to show representative characteristic of conditioning process at fast in the experiment. When the foot was touched continuously without touching robot's belly, the weight became zero again and the touching foot stimulus did not generate emotional response any more. Therefore, the proposed conditioning process could be used for learning temporal relation between stimulus and generation of emotional responses about general stimuli.

VI. CONCLUSION

In this research, the framework for robot's reactive emotions was proposed. Basic reactive emotions for interactive robots were identified through the study on psychological researches about humans' emotions. Computational models to implement the framework in the robot system were also proposed and the working of the proposed models was also verified. Reactive emotional response could be generated according to the stimulus' change with regard to the robot's drive. Even though the proposed model can not generate full fledged emotions for its simplicity and limitation, reactive emotions could work as a mean to make the robot look stimulus aware with the proposed process. Implementing behavioral manifestation after emotional arousal and experiments regarding interaction with human will be the necessary research direction in the future. The reactive emotion mechanism is the beginning to make the interactive robot emotionally responsive, and the proposed framework can be used as a corner-stone of designing computational process for interactive robots.

VII. ACKNOWLEDGEMENT

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