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Cognitive Regulation and Emotion Modeling for Micro-expression

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Abstract

This paper proposed an effective system about micro-expression cognition and emotional regulation. First, the micro-expressional face was mapped into Arousal-Valence-Stance 3D emotion space. The micro-expression recognition is based on 3D-Gradient projection descriptor and the gradient magnitude weighted Nearest Neighbor Algorithm (NNA) in facial feature regions. Second, Gross cognitive reappraisal strategy was introduced to emotion analysis. In this research the emotional regulation process operated in the continuous emotional space enabling a wide range of intermediary emotions to be obtained. Finally, the micro-expression recognition algorithm was tested with the Yale University's facial database. The cognitive emotional system was applied to the human-robot interaction. The experiment results show that this micro-expression cognitive emotional model is generally consistent with human brain emotional regulation mechanisms and efficiently improve robot's emotion humanoid.

Keywords: *Micro-expression, cognitive regulation, emotion modeling, 3D-Gradient projection descriptor, weighted Nearest Neighbor Algorithm*

1. Introduction

Micro-expression recognition comes into being with the development of facial expression recognition (FER) research. It is one of the most powerful, natural and direct way to communicate with each other [1]. As a kind of the spontaneous expression, micro-expression, whose duration is only 1/25 to 1/5 second [2], contains numerous real emotional states suppressed and hidden in the interaction [3]. In 1966, Haggard and Isaacs first discovered micro-expression and perceived that it is closely relate to the self-defence mechanism [2]. Ekman considered that micro-expression contains complete muscle actions as regular expression, and divided micro-expressions into six prototypical emotions: happiness, sadness, surprise, fear, anger and disgust [4]. Henceforth, micro-expression recognition became a new way to understand human real emotions and inner emotional processes.

There are many micro-expression researches based on the geometric feature of feature regions (such as eyebrows, eyes, facial action units). Classification methods, such as Local Binary Patterns from Three Orthogonal Panels (LBP-TOP) feature extraction method, Support Vector Machine (SVM), Random Forest, Multiple Kernel Learning (MKL) et al., are used quite extensively for micro-expression recognition [5]. Polikovsky team adopted a 3D-Gradient histogram method for the feature extraction and classified micro-expressions by pre-established rules [6]. Shreve research group extracted the micro-expressions feature by an improved optical flow method [7]. Moreover, Gabor feature extraction and GentleSVM were used in the automatic micro-expression recognition system [8].

This paper proposed a micro-expression cognition and emotional regulation system. The expression tendency is analyzed by the projection gradient direction histogram for facial feature regions, and the micro-expression key frames are found by the peak area of

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the histogram. This is especially important to deal with HCI system working in real time. Then, the classification and recognition of micro-expression classification is realized by the gradient magnitude weighted Nearest Neighbor Algorithm. Moreover, the main outstanding feature of our work is that the emotional regulation model does not simply provide the classification and jump in terms of a set of discrete emotional labels, but that it operates in a continuous 3D emotional space enabling a wide range of intermediary emotional states to be obtained. Another noteworthy feature of the work is that the system is tested with a cognitive and probabilistic algorithm showing the cognitive and emotional diversity of different individuals. Furthermore, human assessment is taken into consideration in the evaluation of the emotional regulation system. This type of study provides substantial added value in the active field state space to a system that deals with human-computer intelligent interaction flexibly.

The structure of this paper (Figure 1) is the following: Section 2 describes the capture and recognition method of micro-expressions into discrete categories. In section 3 the step from the discrete input stimulus to the continuous emotional space is explained in detail and the above perspective is carefully validated and implemented in section 4. Ultimately, section 5 comprises concluding remarks and description of future work.

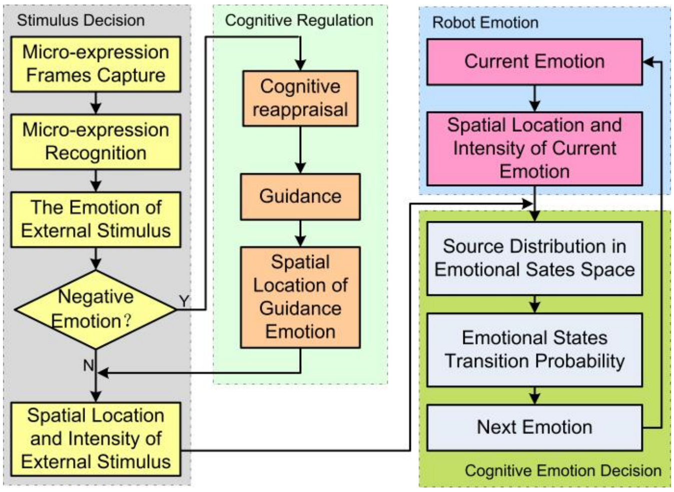

Figure 1. The Structure of this Paper

2. Micro-Expression Recognition

2.1. Facial Feature Regions

Based on Facial Action Coding System [9], this paper chosen some conspicuous action units (AU), such as eyes, brows, mouth et al, in facial gestures as feature regions and ignored unrepresentative units to reduce the calculation time. As is shown in Figure 2(b), 13 feature points were marked on the first frame (Figure 2(a)). There were 1-2 points in a feature region, so the feature point or the connection between points was the region center and the region was in the size of participant’s eye [10]. Here totals 9 features regions. The AU description, position and size of each feature region were provided in Figure 2(c). In general, nose and forehead had slightest changes in all action units, so point C1, C2, and C3 were defined as a discriminant region to judge whether there was a relative displacement between the face and the camera. The entire video stream was divided into many feature cubes in chronological order after the feature region division [11]. Figure 3 is the facial feature region cube of the right eye.

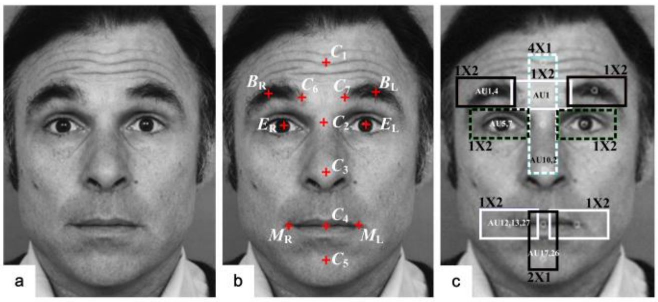

Figure 2. Facial Feature Regions

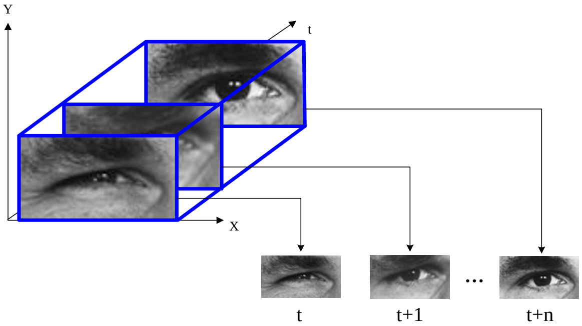

Figure 3. Facial Feature Region Cube of Right Eye

2.2. Micro-Expression Capture

3D-Gradient projection method projects gradient vectors in the XOT and YOT plane of Cartesian coordinate system to transform a 3D-Gradient vector into two plane vectors. So the 3D-Gradient direction is instead of two independent 2D projection direction, θ_{xt} and θ_{yt}. Here, θ_{xt} and θ_{yt} are the pixel's horizontal and vertical movement direction from current frame to the next, respectively. Detailed gradient projection description is as follows. (1) Facial feature cube ($m \times n$ pixels) mentioned in 2.1 are divided into m cross sections and n longitudinal sections. (2) The graph $L(x,t)$ (or $L(y,t)$) composed by X-coordinate (Y-coordinate) and timeline reflects each pixel's movement state really. (3) The magnitude and direction of 2D-Gradient projection vector are shown in formula (1).

$$
\begin{aligned}
m_{xt} &= \sqrt{L_x(x,t)^2 + L_t(x,t)^2} \\
\theta_{xt} &= \tan^{-1}\left(L_t(x,t) / L_x(x,t)\right) \\
m_{yt} &= \sqrt{L_y(y,t)^2 + L_t(y,t)^2} \\
\theta_{yt} &= \tan^{-1}\left(L_t(y,t) / L_y(y,t)\right)
\end{aligned}
\tag{1}
$$

As time goes on time increment $\Delta t > 0$, so $-\pi/2 < \theta_{xt} < \pi/2$ in xot. To facilitate the statistic, θ_{xt} is divided into 6 equal units within its range shown in Figure 4. Each unit contains 3 subunits, a, b, c. Subunit a means the horizontal displacement of pixel between two frames is not obvious. Subunit b means the pixel's change at t direction is similar to at x. Subunit c means the pixel has obvious horizontal displacement between two frames. Similarly, θ_{yt} in yot is consistent with θ_{xt}.

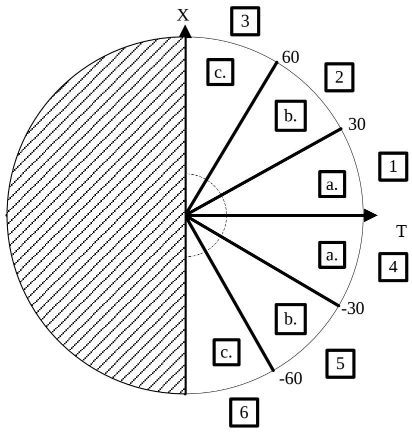

Figure 4. Division of Gradient Projection Direction in xot

Calculate gradient direction of pixels at time t by formula (1). Then group the pixels according to the above method to establish the 2D-Gradient direction histogram. Corresponding to Figure 4, the subunits from θ_{xt} and θ_{yt} of pixels are collected respectively for forming 2D-Gradient direction histogram (as shown in Figure 5). The more pixels in this angle range, the higher this histogram altitude is. The peak of histogram in subunits b and c means there is obvious movement at this moment, namely, micro-expression occurs.

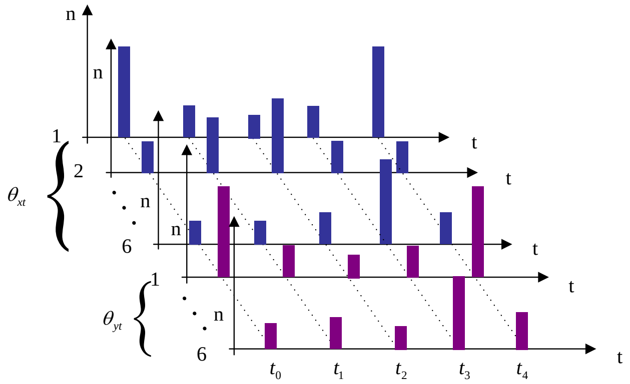

Figure 5. 2d-Gradient Direction Histogram

2.3 Micro-Expression Classification

Nearest Neighbor Algorithm (NNA) depends on limited adjacent samples, so compared with other methods NNA is more effective for the sample set with class fields cross. Accordingly, this paper built a nearest neighbor classifier based on gradient weighting method to classify lower-dimensional LGBP feature.

3D-Gradient is:

$$m_{3D}(x,y,t)=\sqrt{L_x^{\ 2}+L_y^{\ 2}+L_t^{\ 2}} \tag{2}$$

Because there is more discriminatory information in feature regions with large movement range than with slight, micro-expression can be well identified in those large movement regions. Consequently, different weights in different regions will give a more accurate and effective representation about the changes of micro-expression. Based on formula (2), the weight in feature region i at time t is:

$$W_i = \frac{\sum_{(x,y)\in R_i} m_{3D}(x,y,t)}{\sum_{i=1}^{9}\sum_{(x,y)\in R_i} m_{3D}(x,y,t)} \overset{t}{=} \frac{\sum_{(x,y)\in R_i} \sqrt{{L_x}^2 + {L_y}^2}}{\sum_{i=1}^{9}\sum_{(x,y)\in R_i} \sqrt{{L_x}^2 + {L_y}^2}} \tag{3}$$

Introducing weighting coefficient W_i, the NNA of micro-expression feature based on 3D-Gradient is:

$$\sum_{j=1}^{9} d(W_j D_{T,j}, W_j D_{S,j}) = \min_{Q\in[1,n]} \sum_{j=1}^{9} d(W_j D_{T,j}, W_j D_{Q,j}) \tag{4}$$

Here, d is weighted Euclidean distance between test sample $D_{T,j}$ and trained sample $D_{S,j}$. When $D_{S,j}$ belongs to category C_k, $D_{T,j} \in C_k$.

3. Cognitive-Emotional Modeling

3.1. Gross Cognitive Regulation

Gross believes that cognitive reappraisal as an essential part of antecedent-focused strategies always changes individual psychological experience for understanding the negative emotions from the positive perspective[12]. Thus, cognitive reappraisal plays an important role in the human-robot interaction. We can give robot encourage and comfort via language, behavior, expressions and so on to implement the cognitive reappraisal. In this paper, robot can get encourage from participant's expressions. Cognitive reappraisal will trigger the position change of stimulus emotion in the active field. The higher degree of guidance emotion the stronger influence the cognitive reappraisal has. The rule about position change is shown in Figure 6.

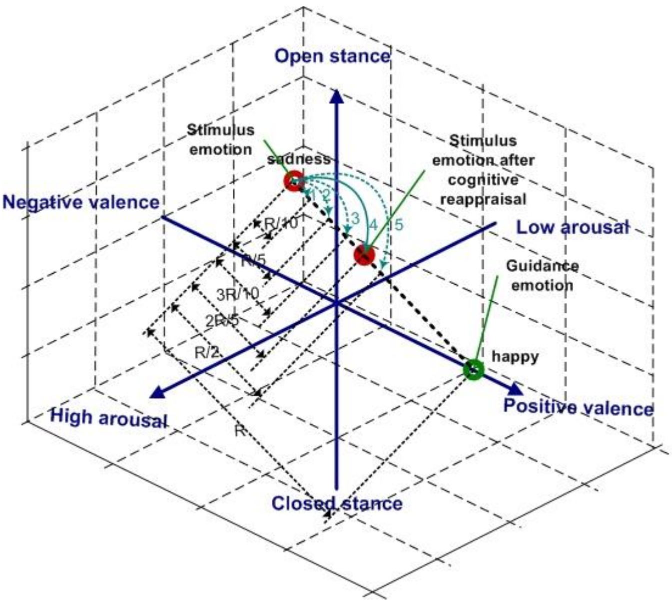

Figure 6. Cognitive Reappraisal Sketch

3.2. Emotional States Interaction

Dynamical psychology shows that human psychology also requires energy (namely, psychological energy), as other physical dynamical systems. So Kismet's emotional space can be built in the active field for describing emotional spatiotemporal property and measuring energy change among emotions. In this emotional model, the interaction between stimulus emotion and robot own emotion in the active field forms the emotional state space. The activated intensity of emotional state determines source size and the emotional category determines source position. Field intensity distribution in the emotional state space is determined by the emotional state system which is composed of stimulus states and own states.

Emotional potential ε describes the filed from energy, so the emotional potential energy is represented by ε's value which is only determined by field sources. The computing method about emotional potential energy $M(x,y,z)$ having n activated emotional states is (Figure 7):

$$\varepsilon_M(x,y,z)=\sum_{i=1}^{n}\frac{Q_i}{\mu r_i}=\sum_{i=1}^{n}\frac{Q_i}{\mu\sqrt{(x-x_i)^2+(y-y_i)^2+(z-z_i)^2}} \tag{4}$$

Where i is the number of emotional sources, r_i is the distance from emotional source i to point $M(x,y,z)$, μ is a coefficient, and Q_i is the intensity of emotional source i.

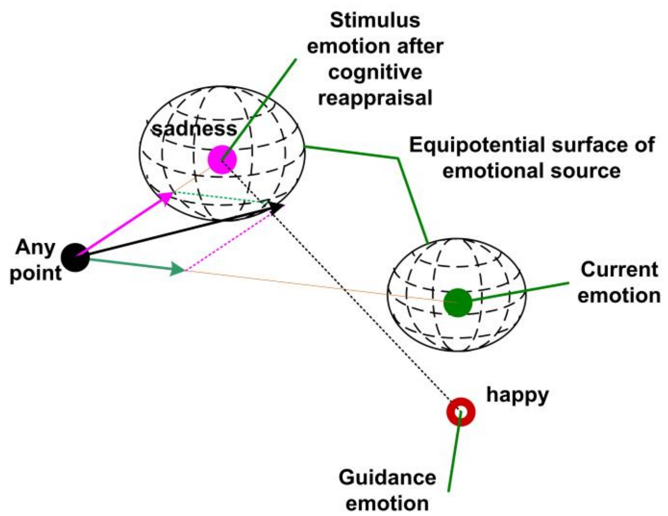

Figure 7. Emotional States Interaction in Active Field

3.3. Emotion Modeling Based on HMM

Human emotional regulation can be divided into two steps, the first step is basis of cognitive reappraisal and the second is correlated with personality factor. So this paper regards emotional regulation process as a double stochastic process, namely, Hidden Markov model (HMM).

Emotional states with equal psychology energy have same transition probability, and they are perceived as a family of emotional states. In the hidden process, ε_t is the psychological energy of emotional family $S_t^{'}$ at time t, $t>0$. After the cognitive reappraisal, emotional regulation can be considered as a stochastic process with continuous space and time. π which is decided by the final state of last regulation is a probability matrix of initial state. $P_{ij}=\varepsilon_j/\varepsilon_{sum}$ is the transition probability from emotional family i to j. This Markov process is used to expound the transition among emotional families.

Another stochastic process is used for outputting specific emotional state which can be expressed by some symbols such as expression, language, behavior etc. However, these symbols all are emotional extrinsic manifestations and the emotional state is the motivation to them. Considering the emotional diversity and system real-time, 26 direction (namely, 26 emotional states) shown in Table.1 are selected from an emotional family. The angle from the high arousal axis is θ, $-\pi \le \theta \le \pi$. The angle from arousal-valence plane is φ, $-\pi/2 \le \varphi \le \pi/2$. And the angle between possible direction v and the linkage between own emotional state and stimulus state is defined as σ_v. Emotional state transition probability $P_v^{'}$ is decided by the angle σ_v.

$$P_v^{'} = \frac{\pi - \sigma_v}{n\pi - \sum_{v=1}^{n} \sigma_v}, \; n = 26 \tag{5}$$

Table 1. 26 Possible Direction of Emotional Sates

	1	2	3	4	5	6	7	8	9	10	11	12	13
θ	0	$\frac{\pi}{4}$	$\frac{\pi}{2}$	$\frac{3\pi}{4}$	π	$-\frac{\pi}{4}$	$-\frac{\pi}{2}$	$-\frac{3\pi}{4}$	0	0	$\frac{\pi}{4}$	$\frac{\pi}{2}$	$\frac{3\pi}{4}$
φ	0	0	0	0	0	0	0	0	$\frac{\pi}{2}$	$\frac{\pi}{4}$	$\frac{\pi}{4}$	$\frac{\pi}{4}$	$\frac{\pi}{4}$
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
θ	π	$-\frac{\pi}{4}$	$-\frac{\pi}{2}$	$-\frac{3\pi}{4}$	0	0	$\frac{\pi}{4}$	$\frac{\pi}{2}$	$\frac{3\pi}{4}$	π	$-\frac{\pi}{4}$	$-\frac{\pi}{2}$	$-\frac{3\pi}{4}$
φ	$\frac{\pi}{4}$	$\frac{\pi}{4}$	$\frac{\pi}{4}$	$\frac{\pi}{4}$	$-\frac{\pi}{2}$	$-\frac{\pi}{4}$	$-\frac{\pi}{4}$	$-\frac{\pi}{4}$	$-\frac{\pi}{4}$	$-\frac{\pi}{4}$	$-\frac{\pi}{4}$	$-\frac{\pi}{4}$	$-\frac{\pi}{4}$

4. Experiment

4.1. Experiment and Analysis for Micro-Expression Recognition

Experimental data derive from participants' video in human-robot interaction. The sampling frequency is 25 frame per second. We input a video contained micro-expression. The histogram of horizontal gradient direction angle about 20 frames of the video is shown in Figure 8. The histogram of vertical gradient direction angle is in the same way. First, the peak of 2 and 3 angle regions is in frame 6 to 10 means that pixels in this feature region has obvious change of gradient at this moment. This corresponds to muscles of mouth corner gradually tightening in the frame 4 to 10 shown in Figure 9. Then the peak of 5 and 6 angle regions is in frame 16 to 18, however, the direction is opposite to frame 6 to 10. This indicates that pixels in these feature regions have obvious change of gradient in fame 16 to 18, and this change is a muscle release process shown in frame 15 to 18 in Figure 9.

Motion curves of horizontal and vertical direction are drawn by tracking feature point M_L shown in Figure 9. From Figure 9, horizontal and vertical motions are in sync. In addition, M_L sharply changes on the two direction at about 0.18s respectively, and reaches its peak at 0.42s. This means that an micro-expression appears at about frame 10 to 11, and it almost coincides with the preceding results of simulation described by 3D-Gradient Projection completely. Thus, the micro-expression capture algorithm mentioned in section 2.1 and 2.2 is effective.

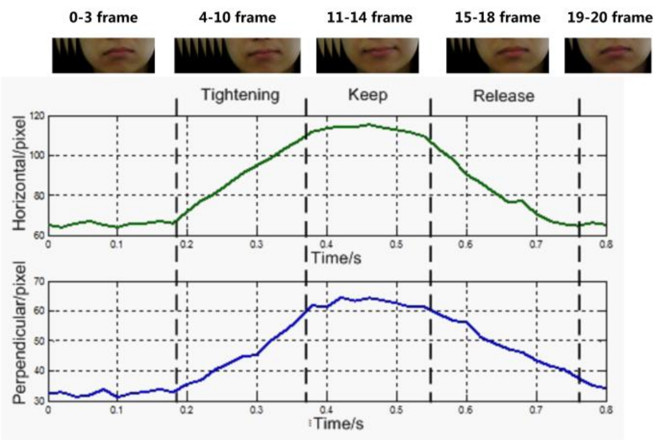

Figure 9. Feature Point M_L'S Motion Curves

The training images for micro-expression classification come from Yale University's facial database. They include six prototypical emotions, and each emotion has ten different images. The size of sample window is 30×12 pixels and gray level is 16. In our experiment, 72 micro-expression images, which are captured by the above method, are classified by equal weights and 3D-Gradient weights algorithm respectively. Their ROC curves[13] are shown in Figure 10. From the experimental results, both curves have better convergence property, but the area under the 3D-Gradient weights curve is larger than the equal weights. This illustrates that NNA based on 3D-Gradient weights is superior to equal weights. Furthermore, the curve's starting point of NNA based on 3D-Gradient weights is higher than equal weights. It means that the sensitive indicator of NNA based on 3D-Gradient weights is better, namely NNA based on 3D-Gradient weights has well capability.

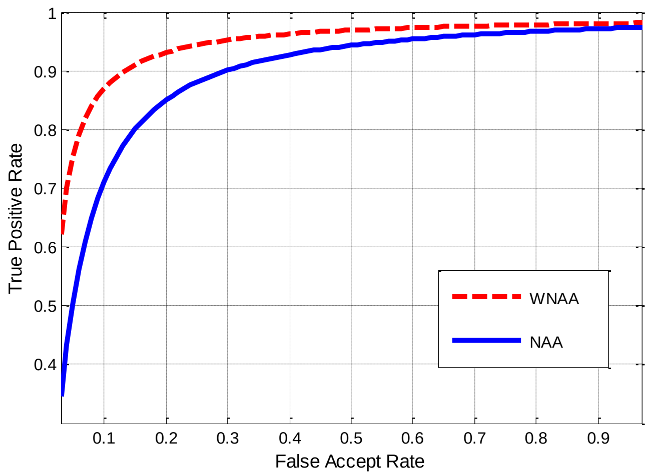

Figure 10. Roc Curves Equal Weights and 3D-Gradient Weights Classification Algorithm

4.2. Emotional Regulation Experiment and Analysis

The method described in the previous section has been put into practice with the outputs of the pre-existing robot systems [14-15] when applied to the video contained micro-expressions. Figure 11 shows the robot emotional regulation process with two different initial emotional states, a positive emotion and a negative emotion. In 0-1 minute, robot own emotion remained without external stimulus. At the 60s, an external stimulus "disgust" derived from micro-expression occurred, so robot emotion's negative degree gradually increased during 1-2 minute and achieved the balance around the 120s. Then this emotional experience was with the robot for about 1 minute. Because the "disgust" stimulus has disappeared a while, robot emotional state gradually trended to "Calming" during 3-4 minute. At the 240s, an external stimulus "happiness" derived from micro-expression occurred, so robot emotion's positive degree gradually increased during 4-5 minute and achieved the balance around the 250s. Then similar emotional experience was with the robot for about 1 minute, and gradually waned since 360s. In contrast to the positive initial emotion, the negative one has weaker resistance to negative external stimulus like "disgust" in the experience, although they are all transfer to a more negative emotion in the emotional space. And compared with the more negative emotion, the more positive one is easy to significantly improve when a positive external stimulus occurs, such as "happiness" in the 240s.

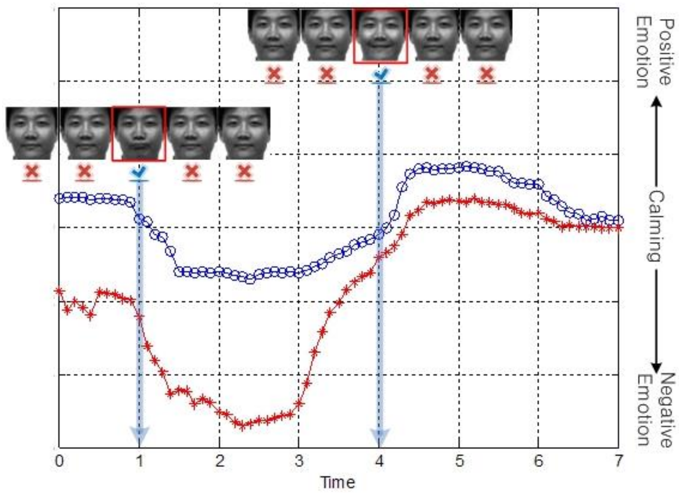

Figure 11. Robot Emotional Regulation Process

To verify the Gross cognitive regulation, we experiment with and without guiding cognition respectively. Figure 12 shows the robot emotion regulation process with sadness stimulus and happiness guiding cognition. In the beginning, robot was in a clam state. When the sadness stimulus occurs, the emotion was changed to be heart-breaking and sobbed loudly. However, the actual emotion state was really not this intense because of the positive guiding and the response suppression.

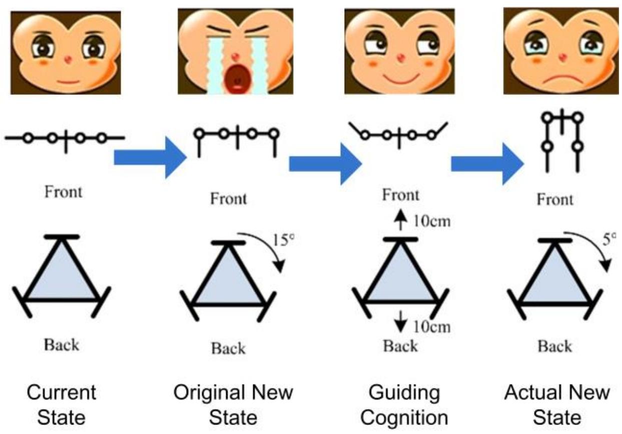

Figure 12. Cognitive Regulation

5. Discussion and Conclusion

This work shows an emotional regulation method based on micro-expression cognition. The inputs to the system are a set of facial expression video. The micro-expression is captured in a simple way in real time with relevant feature information. The system integrates the gradient magnitude weighted into Nearest Neighbor Algorithm (NNA) for classification robust, and maps micro-expressions into six prototypical emotions and "calming". The noteworthy feature of the emotional regulation work is that it is out of the simply interactive mode providing the classification and jump in terms of a set of discrete emotional labels, and it operates in a continuous 3D emotional space enabling a wide range of intermediary emotional states to be obtained under the external stimulus. Moreover, this system focuses on the research of emotional regulation with cognition and proposes a micro-expression cognition and emotional regulation model based on Gross reappraisal strategy. Gross cognitive reappraisal strategy effectively decreases negative emotion experience and behavioral expression, and provides a more intelligent cognition style to computer/robot acted as a positive role in HCI. We use HMM a double stochastic process for making robot emotions more diversification in human-robot interaction.

Results are very satisfactory, although in order to have more humanoid emotion the kind and extent of external stimulus emotion could be increased. This problem is partially overcome by doing continuous facial emotional classification, i.e. using an expansion method makes the discrete facial emotion to a dimensional description [16]. The recent focus on the research of affective-computing relies on sensing emotions from multiple modalities, because natural human-human interaction is multi-modal: people communicate through speech and use body language, such as posture, facial expressions, and gaze, to express emotion. But our works only considers a respect micro-expression to capture the emotional state [17-21]. In addition, the model of reappraisal strategy makes emotional cognition analysis with only two preset parameters, so if the more thorough cognitive reappraisal strategy is used, results are more nature and effective. The literature reports many attempts to find out correspondences between nonlinear dynamic system a psychological responses and expects to achieve emotion modeling in infinite dimensional space, although they are only exploration in HCI far from a clear mathematical interpretation[22-24]. Our findings only propose a computable emotion model justified on psychological significance in continuous space, but without completely explain any specific theory. Following from this, future works could be oriented to the study of nature inspired cognitive-affective computing by means of emotion modeling in continuous active space, especially pay attention to the multi-modal external stimulus and the pervasive emotion computing.

Acknowledgements

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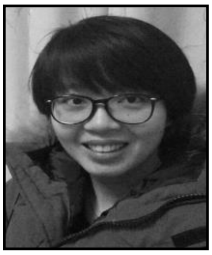

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