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Cognitive and Emotional Structure of a Robotic Game Player in Turn-based Interaction

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Abstract

This paper focuses on how cognitive and emotional structures affect humans during long-term interaction. We design an interaction with a turn-based game, the Chopstick Game, in which two agents play with numbers using their fingers. While a human and a robot agent alternate turn, the human user applies herself to play the game and to learn new winning skills from the robot agent. Conventional valence and arousal space is applied to design emotional interaction. For the robotic system, we implement finger gesture recognition and emotional behaviors that are designed for three-dimensional virtual robot. In the experimental tests, the properness of the proposed schemes is verified and the effect of the emotional interaction is discussed.

Keywords: *Cognitive and Emotional Structure, Emotional interaction, Chopstick Game, Turn-based interaction*

1. INTRODUCTION

In many robotic applications, human-robot interaction (HRI) has been noticed as a powerful tool that humans can use to interact with robotic systems. Considering that most robots have a variety of modalities that are different from those of human organs, mutual understanding of both agents is a prerequisite for natural interaction. During HRI, each agent is capable of understanding shared grounds and the interaction continues with context flows that are composed of shared grounds [1].

As an extension of the shared ground concept, when a human starts to interact with an unknown robot, he or she does not feel familiar with unknown capabilities of the robot before realizing the functions of the given shared grounds. Even in the case of a humanoid robot, the robot's unnatural modal communication and gestures will require the human to structure the shared grounds at the earliest stages.

In the case of a service robot, the major task is to provide proper tasks to humans. However, human sometimes feels difficulties when faced with new types of interaction. For example, a cleaning robot requires information about when or where it should start a cleaning task, and a human user must determine the control commands through touch buttons or a remote controller. Thus, a new buyer often misunderstands that a robot will perform the cleaning task automatically. Without considering the performance of the task execution, these kinds of passive interactions that depend on human judgment or include unfamiliar interfaces impede the progress of the robotics market, because most human believe that robots will simply do everything on their own.

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From the viewpoint of mutual understanding, scenario-based interaction is an alternative way to compensate for any lack of modal information. When a human joins a scenario, a robot is easily aware of the human's response and can design proper actions according to the scenario. For this reason, game-based interaction has been preferable for the design of long term interaction.

On the other hand, emotional interaction, which is artificially generated by observing humans emotion and by providing proper responses, has been regarded as an alternative method for intuitively improving human familiarity with a robotic system.

In emotional interaction, a robot does not provide physical services; rather, it provides emotional services for the treatment of dementia and emotional therapy [2, 3]. For peoples who are exposed to many computer games and virtual avatars, emotional expression becomes habituated without considering its properness. Seemingly, humans already have common grounds of emotional interaction with artificial agents.

However, when a service robot has as its major functions tasks such as education or instruction, the role of emotional interaction is questionable. On the other hands, we focused on the idea that emotion interaction could be a supplemental function to make up for the lack of a major service function or could be restricted within the entertainment area or to the emotional therapy.

In many cases, emotional interaction is exaggerated because a robotic system has limited modalities and resources. Also, to avoid the uncanny valley that results from the limitation of modal expression, a simple mechanism and electrics is preferable for intuitive and exaggerated emotional communication [4, 5].

This paper focuses on the role of emotional interaction that is provided as supplementary tools for a robot. In an education service robot, the quality of the human's learning becomes dominant. As mentioned above, it is evident that the emotional interaction improves human's familiarity and absorption [6,7,8]. However, after a series of interaction that is sufficient for human adaptation, we pose the question of whether any sort of exaggerated robot emotion is still necessary and efficient.

In this paper, we design a robotic game player that has preknowledge of efficient game tactics. The Chopstick Game, which has become popular in recent years, has enough degrees-of-freedom for humans to have difficulty in predicting its results. We attempt to design a robot instructor that can bring humans to learn unexpected tactics. When a human joins the turn-based scenario, emotional interaction is executed for improving familiarity and naturalness. Assuming that a robotic player will have more skillful tactics with the help of its repetitive searching method, the role of emotion in educational interaction will be compared for a beginner group and a skillful group.

2. TURN-BASED INTERACTION DESIGN

Most elementary students learn the basics of numeric operation. For educational purposes, many types of simple board games have been developed for students to enjoy learnings. The Chopstick Game is a popular one in Korea. Both players start with two fingers that look like a pair of chopsticks, as depicted in Fig. 1.

The basic rule concerns the overall sum of the players' fingers. At the initial stage, the two players start with two fingers and one can add fingers to those of the other player by touching that player's hand. When the total finger number on each hand is larger than or equal to five, the finger number goes zero. Therefore, when a player has zero finger number on both hands, he or she loses the game. It is a touch-and-add operation.

Fig. 1. Chopstick Game with two agents

One interesting feature is that a player can merge finger numbers by clapping her hands and splitting the overall finger numbers on both hands. As expected, the basic play with the touch-and-add operation becomes monotonous after a series of turns. However, the merge-and-split operation, which causes confusion in any estimate of the future results, supplements the game with variety and complexity. In other words, this game is intuitively easy to learn but most human think that the game is complex in terms of learning the game tactics.

There are two features for the design of game strategy: the looped state transition and the optimality of having a large finger number. When a human puts in three fingers on both of his or her hands, this state can be described with the vector (3, 3); the player renews the states with (1, 0) or (2, 4) because the sum of the finger numbers is six. In the former case, a small finger number with one or zero is often repeated in the earlier stages. The game status suddenly changes in other stages and it is difficult to predict future results. Furthermore, the frequent looped situation makes it difficult for the game players to choose the optimality because large finger number is useful for attack but is weak for defense.

3. ANALYSIS OF CHOPSTICK GAME

There are two features that are conductive to the design of a winning strategy: local optimality of how a player can maintain a large finger number for defense and attack, and how a player changes the game situation by means of the merge-and-split operation.

Simply, the finger number has a two-sided function. A small number is better for a defense but not for an attack. One possible tactics is to maintain a large number without losing due to the other player's next attack. The strategy is relevant only for the touch-and-add operation. Without the merge-and-split operation, the best action is to create an estimate using a global searching method. Every possible action can be simulated and the overall set of possible scenarios can be used to estimate the future cost.

The merge-and-split operation has sufficient degrees-of-freedom to shift the game state and to even the state in the earlier stages. When the finger number is less than five, an adverse state with a highly large finger number can be changed through the merge-and-split operation. Therefore, a process of turning back to the earlier stages frequently occurs and this is an efficient method for winning a game.

For example, when a human puts in three fingers on both of her hands, this situation can be described with the vector *H;(3,3)*. When the robot puts in one finger from each hand, this situation can be described by the vector *R:(1,1)*. The human can merge and splits the current state with *H':(1,5)*→*(1,0)* or *H':(2,4)* because the sum of the finger numbers is six. In the former case, the sum of the two fingers is small such a situation is better for defense. In the latter case with *R:(1,1)*, the attack from the robot makes *H'':(2,0)* and the human effects a turn back to the initial state with *H'''(1,1)* via the merge-and-split operation. In this manner, the game state turns back to the previous states via the merge-and-split operation.

However, a large finger number depends on the other player's hand state. Supposing that the human has *H:(1,1)* and a robot has *R:(1,0)*, a robot seems to have small finger number. However, when the robot performs the touch-and-add operation, the human has *H':(1,2)*, which is transitioned into *H'':(3,0)* by the merge-and-split operation. Because the robot has put in only one finger, the next human state becomes *H''':(4,0)* and the human wins the game by touching four fingers to the one finger of the robot.

During the analysis of the Chopstick Game, we found that perfect future cost estimation cannot be achieved. The merge-and-split process leads to many repeated cases that are recursively concatenated with other cases. This is a different feature compared to other board games such as Gammon or Tic-Tac-Toe [9,10]. The Chopstick Game has a feature similar to that of the game Go [11], by which the looped structure makes the human players confused when estimating the future cost.

For this reason, we have designed a strategy for designing Chopstick Game tactics. Basically, we assume that tge Chopstick Game is composed of several sub games governed by the touch-and-add operation; the merge-and-split operation is considered as a new starting point for each sub game. As mentioned before, this operation creates a new sub game in which the touch-and-add operation can be optimized.

The game state is defined as $s=[H_L, H_R, R_L, R_R]$, each of which indicates the numbers of fingers put in by both of the agents. *H* and *R* denote the human and the robot, and the subscrips L and R indicate the left and right hands. At the initial tate, each agent has one finger number on both hands. Thus, the state is defined as *s*=[1,1,1,1]. Also, from the game rules, each finger number is an integer bounded by [0, 4].

For a given state, an agent has four possible actions a=[*LL*, *LR*, *RL*, *RR*] for the touch-and-add operation. For example, the human can touch and add a finger number from the left hand to the other's left hand (*LL*) or right hand (*LR*), and from the right hand to the other's left hand (*RL*) or right hand (*RR*).

When the robot agent wins a game, a positive reward is given. Contrarily, if the robot agent loses a game, a negative reward is given. Considering that the Chopstick Game has a looped structure, winning in a shorter number of turns is favorable. Thus, the discounted return using a gamma ratio is applied to estimate future reward.

For the development of game tactics, the robot agent tries to estimate the maximum *Q(s,a)* value as is done in the case of reinforcement learning. In addition, because the human player has joined the game, the robotic agent assumes that the human will choose the best action. Thus, from the viewpoint of the robot agent, the minimum *Q(s,a)* value represents the value for the human's turn. The overall estimation can be defined as in the following:

$$Q(s,a)=\begin{cases} r(s,a)+\min\limits_a Q(s',a) & (s\in Human's\ turn) \\ r(s,a)+\max\limits_a Q(s',a) & (s\in Robot's\ turn), \end{cases}$$

where r is a observed reward, a is an action, and s' is the next state. The merge-and-split operation is the key strategy for winning a game. However, the game has an open state space caused by its looped structure; its optimality is very difficult to obtain in many cases. Thus, we suggest that all possible merge-and-split operations be considered as new sub games and their future rewards be calculated.

The finger numbers of the robot agent are defined as RL and RR. Possible candidates for new finger numbers must satisfy the following condition.

$$S = R_L + R_R,$$
$$I \in [0, S]$$
$$\therefore R_L' = Mod(I, 5)$$
$$R_R' = Mod(S - I, 5).$$

The Mod is the modulus operation because the maximum finger number is five. The pseudo code of the overall set of tactics is described in Table 1.

Table 1. Pseudo code of Chopstick Game tactics

With a given state $s = [H_L, H_R, R_L, R_R]$
M = FindMaxQ(s) with possible actions including LL, LR, RL, and RR.
S = $R_L + R_R$
For I=0 to S
s' = $[H_L, H_R, R_L', R_R']$
m = FindMaxQ(s')
if m is larger than M' then M' = m
End
If M' is larger than M then return merge-and-split.
Else return touch-and-add.

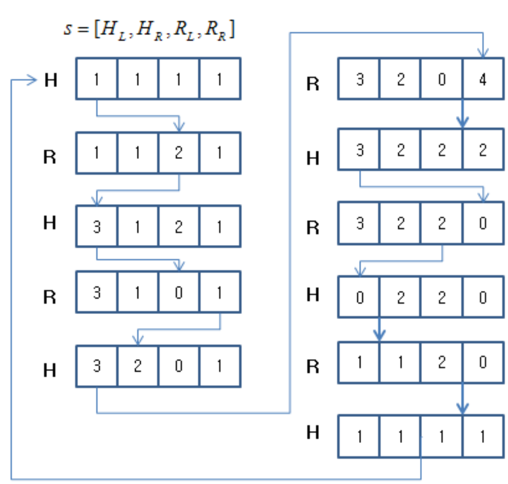

Fig. 2. State transition of Chopstick Game

4. EMOTIONAL INTERACTION

The proposed interaction has certain advantages because a turn-based interaction forces the human to continue the interaction until the end of the game, and the robot agent is aware of the situation changes as the proposed scenario proceeds.

During Chopstick Game play, the robot observes the human's status by monitoring game status, not by using modal information. In addition, it has design convenience in that the possible cognitive and emotional responses are defined for game player: a winner will usually be happier than a loser.

In conventional emotional interaction, valence and arousal are the common factors used to define the emotional status [12]. In spite of this, valence and arousal have the uncertainties when they are used to define aspects of different case studies. Thus, we attempts to map the several factors associated with the Chopstick Game into valence and arousal values. According to cognitive subsumption theory [13], unencountered information is brought into an agent with respect to agent's current status. Additionally, the emotion status is not continuously determined following valence and arousal space, but can suddenly change when it approaches specific regions. Thus, we attempt to combine conditional acceptance according to cognitive subsumption theory and the catastrophic nature of emotional transitions.

The future reward in each turn is a possible factor for the valence model. When a robot agent estimates future rewards, it marginally predicts the current status of whether the game is going on in a positive way. However, the optimality of Chopstick Game tactics does not continuously proceed owing to the merge-and-split operation.

For a robot to be in an emotional mood, the future reward is added into an artificial valence value. In this manner, the future reward that will results from long-term interaction guides the robot to perform the next action to winning the game, but the observed reward does not produce the emotional changes directly.

Arousal indicates an internal status of being reactive to stimuli. For the design of a robot that can be a game partner, the positive value is defined as the turn numbers; the negative value is proportionally defined as the human's mistakes. The arousal is defined as the summation of the positive and negative values in every turn.

In Fig. 3, the valence and the arousal are mapped with a consideration of the turn increment. About fifteen turns are required for a human beginner and more than forty turns are needed for a skillful human. Thus, the valence and the arousal factors are saturated.

For a human to be immersed in the turn-based interaction, we predesigned behavioral gestures that commonly occur during the game plays. Excitation, tiredness, depression, relaxation, happiness, delight, anger, and depression are the candidate emotions for the robotic player. In the domain of the valence and arousal model, when a robot wins a game with high arousal fired by many playing turns, the emotional state becomes delight. However, with low arousal caused by a few mistakes of the human, the emotion state becomes relaxation even when the robot wins the game.

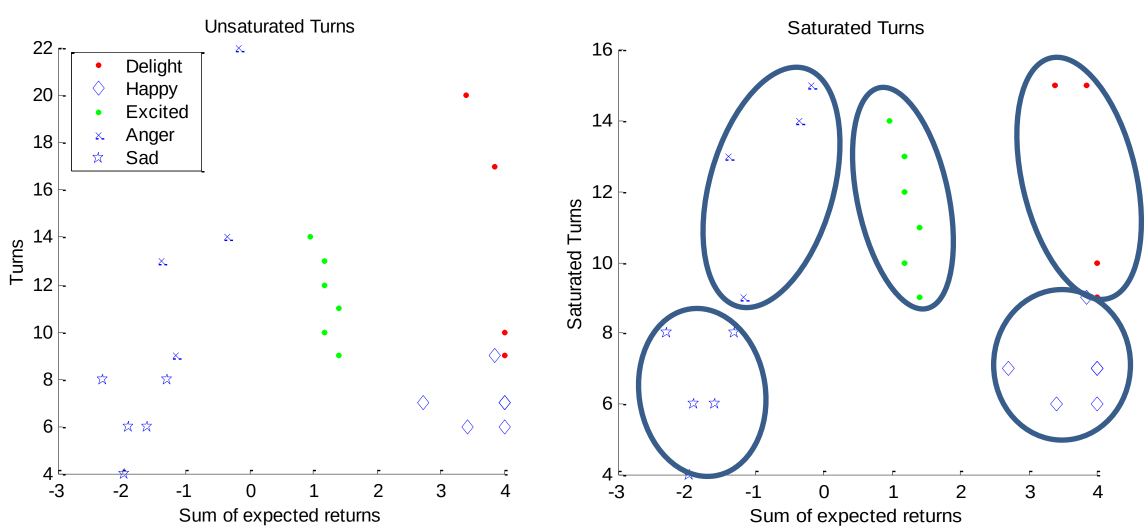

Fig. 3. The emotions with positive arousal are mapped on expected returns and turns that are similar to conventional valence and arousal

5. SYSTEM DESIGN

The proposed robotic game player is designed with three major parts for the implementation of the robotic system. We design the robotic system to recognize the human’s finger number and touch motion, to express the robot’s fingers and its emotional gestures through a three-dimensional virtual agent, and to control tactics.

The human’s finger number depends on the shape of the fingers and their relative positions. Fingers have three joints, which come between distal, intermediate, proximal, and metacarpal bones. When a finger is folded, the direction of distal and proximal is reversed. The thumb is different from the other four fingers. The direction of the distal bone is to the inside of the palm.

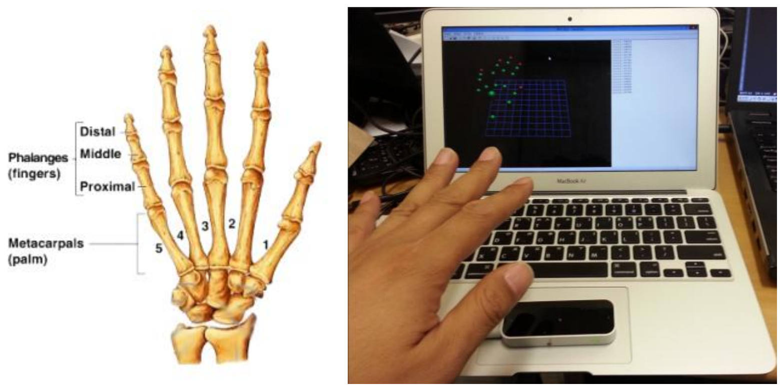

Fig. 4. Finger bones (left) and Leap Motion sensor (right)

For finger counting gestures, the position of the human fingers and its skeleton information are gathered by the Leap Motion sensor, which is specialized for tracking human fingers in three-dimensional space. Instead of providing an accurate position estimate, the skeleton information is not sufficient for counting finger numbers. For this reason, we propose two features: the dot product between the distal and proximal bones, and the relative distance from the thumb to the middle fingers. The feature vector is defined as follows:

$$f = \begin{pmatrix} d_{distal} \cdot d_{proximal} \\ | x_{thumb} - x_{middle} |^2 \end{pmatrix},$$

where **d** is the direction vector and **x** is the position of the finger tip.

As shown in Fig. 4, the index finger, which is often used to describe the finger number one, is confused with two fingers because the skeleton of the thumb is often confusing for the Leap Motion sensor. When the thumb is folded, its bone structure is less easy to detect than when it is in its distal position. Therefore, the distance between the thumb and the middle finger is used to recognize finger gestures. This feature is also relevant for classifying different methods of finger counting. For the expression of three fingers, Asians generally fold in the fourth and the fifth fingers, whereas Americans hold the thumb and the index finger. The Bayesian classifier shows more than 98% successful results.

The robotic player in the proposed interaction is designed as a humanoid. The Chopstick Game player requires two arms with ten fingers to express the touch-and-add and merge-and-split gestures. The arm is required for the touching and merging gestures for the human to recognize if the robot is attempting to add a digit or is preparing to split the fingers. Also, the fingers are necessarily for expressing the finger numbers.

In addition, emotional status is described by the robotic facial expressions. From the arousal and the valence spaces, several cognitive and emotional feelings can be expressed. Eye direction, lid movement, and mouth movement are combined to express disappointment, happiness, boredom, sadness, and so on.

The movement of the virtual agent is based on kinematic movements. The joint trajectories are designed to express the desired movements. Each joint variable is controlled by the proportional gain of the joint error. Thus, the position control guarantees exponential convergence.

However, when there is no gesture expression command, the robotic movements seem monotonous. Thus, an idling motion is designed by relaxing the muscle tension. The sinusoidal variance is also superposed to improve the human-like smooth gestures expression. Also, eye blinking and variant eye gazing are efficient to express an idling gesture.

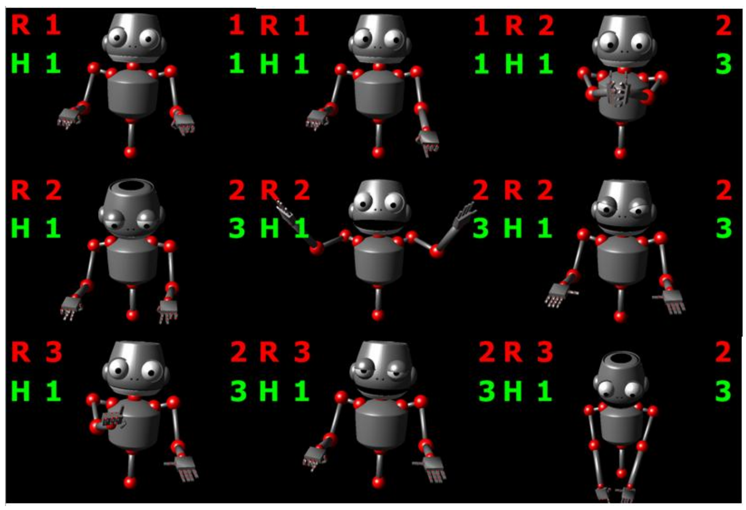

Fig. 5. Variety of emotional expressions: Chopstick Game mode, touching with left hand, merge-and-split motion (top), sadness, delight, excited (middle), happiness, tired, and weak happiness(bottom)

6. CONCLUSION

In this paper, we attempt to verify the role of emotional interaction as a supplemental function to achieving other purposes. A turn-based game is applied for human to join and to follow a pre-known scenario. By playing a game with a robotic player, a beginner naturally learns how to play the game and a skillful human starts to mimic and to adapt to new tactics.

For the development of the robotic player, the Chopstick Game is analyzed using a robot playing with very good tactics. From the difficulties of the looped structure, we propose a suboptimal strategy with a Q-value approach in sub games and with a search for possible merge-and-split operations.

Human finger recognition is executed using the Leap Motion sensor. The uncertainty of skeleton information is compensated for using the dot product and the distance features. The human finger number is accurately recognized through the proposed feature and classifier.

The virtual robot agent is implemented in a three dimension environment. This is a humanoid that has two arms with ten fingers and that can also make the facial expressions. For the improvement of natural interaction, an idling motion based on the sinusoidal function is applied.

The cognitive and the emotional structures are designed under the concept of valence and arousal space. Expectations of winning, which are deterministically estimated, increases and decreases the overall valence value. Increments of turns and human mistakes are applied to adjust arousal factors. The properness is verified through several experiments.

Above all, this paper attempts to answer the question of how efficient emotional interaction is for designing other interactions. The experimental results seem to show the idea that emotional interaction is helpful for humans to feel familiarity but is not crucial for helping with other types of interaction.

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