Study on Emotion and Behavior Generating System based on Facial Expression Recognition

(顔の表情に基づいた感情と行動を表出するシステムに関する研究)

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Chapter 1

Introduction

This chapter presents the background, problem of the research that regards the robot behavior based system with the human expression and robot recognition system. The objective and contribution is to develop a Consciousness-Based Architecture system combining the brained inspired method, which can generate and archive more complexity of the robot emotion and expression based on the robot emotional state that depending the animal perception and human emotional expression. Finally, this chapter introduces the remaining chapters.

1.1 Research background

In recent times, the fast improvement of next generation has produced robots for various purpose and most useful for industrial factories (industrial robots) however also for museums, houses, healthcare establishments and so forth (non-commercial robots). There are numerous types of non-business robots inclusive of carrier robots, welfare robots, healing robots and home robots. In Fig. 1-1 that presents the global robotics market growth; this information has been gleaned from the Japan Robotics affiliation. The market for a carrier and personal robots is anticipated to grow an increasing number of inside the future ("Global Service Robotics Market to Reach US$38.42 Billion by 2015, According to New Report by Global Industry Analysts," n.d.). Those robots are designed with artificial intelligence (AI) to build the robotics machine that can operate in the advanced tasks and attempting to imitate human behavior or cognitive system. The capability of Human-robotic interaction (HRI) also involves the service robot because the robot is necessary to obtain the task or command from user. Therefore, HRI performs an essential position in contemporary autonomous robots. It also usefully perform necessary service tasks around the house for example in home such vacuum robot, entertaining robot, service some task at home.

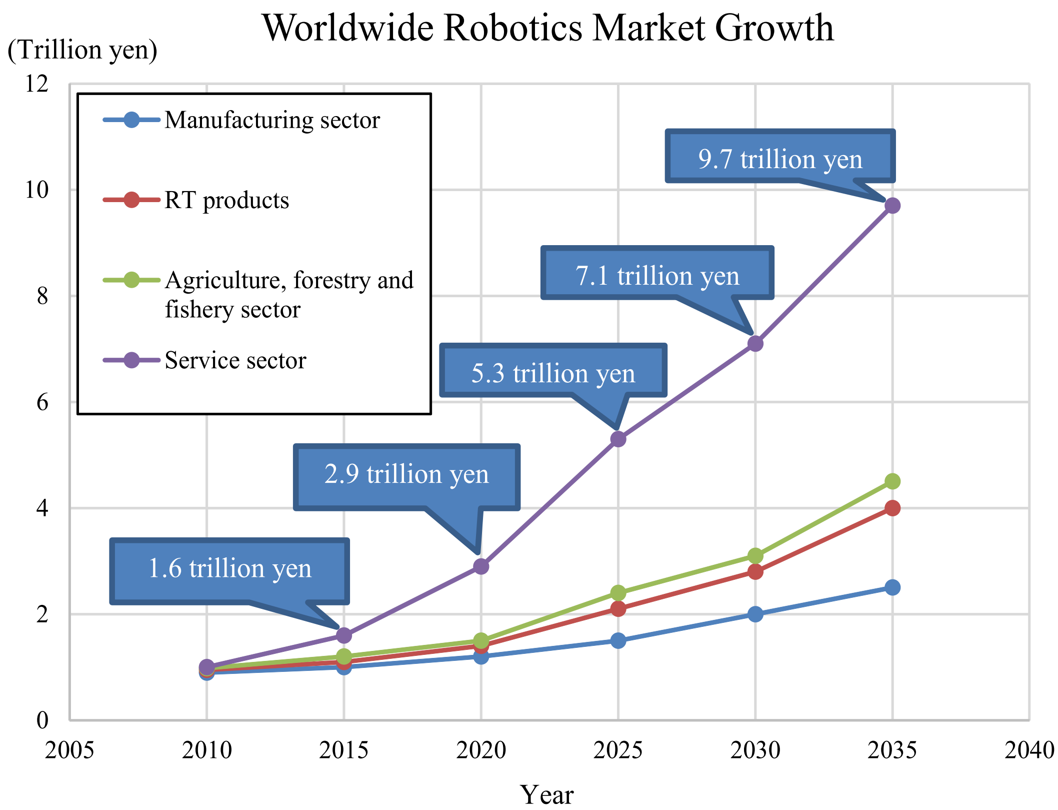


Fig. 1-1 Worldwide Robotics Market Growth. The above diagram shows the importance of robotics in the service sector of industry. Private and government are investing revenues in the industry for the further development in the long time.

HRI requires that robots no longer most effective passively get hold of facts from the surroundings, and can make proper decisions and actively exchange in varying environments, therefore functioning more autonomously and intelligently (Breazeal, 2004; Fong et al., 2003; Kiesler and Hinds, 2004). Nevertheless, designing robots are able to have interaction with humans that is nonetheless a massive venture, as an example, demonstrates cognition in complex surroundings, allow movements to be selected autonomously, or models emotional expression and smooth communique. In this attitude of the robot with emotion or combination of machine and emotion or affective capacity, that seem interest in the research in recent such a robot with cognitive behavior-based(Arkin, 1998; Bongard, 2013; Richter et al., 2012). Regarding this trend, McCarthy's research has described beginning the essential features of robots have to have a consciousness, introspective knowledge, and some philosophy to carry out inside the commonplace-feel international and to accomplish duties efficiently (McCarthy, 1995).

Present-day technology can improve the quality of human life by adding convenience and entertainment, saving time, making it easier to get an instant solution for problems, and even providing therapy. The technology of computing has allowed the development of important tools, including embodied artificial machines — i.e., robots — which can be designed to execute one or more tasks automatically for various purposes. Robots have become increasingly more present in humans' lives, in industry, healthcare, education, agriculture, space, and particularly in the service sector and in our homes (Halal, 2008). The greatest growth in the robotics market is currently for applications in the service sector, and the technology of information computing toward this end is rapidly improving (Lechevalier et al., 2014; Shukla and Shukla, 2012). We are thus concentrating our research on service robots — including personal and social robots — as such robots can make significant contributions to everyone's quality of life (Leite et al., 2013).

Our focus is on improving personal robots that will need to join the operation with humans. The communication between humans and a personal robot will be improved if the robot can engage in emotional recognition and expression with the humans. Because human beings comprehend each other’s' feelings predominantly by recognizing others' emotions expressed by their facial expressions, a personal robot should also be able to comprehend (and provide its own) facial expressions correctly. Accordingly, we have designed a robot that can recognize both its surrounding environment and human expression. We achieved this by building on the foundational research in the study of human-robot interaction (HRI).

The study of personal robot or service robot is an interdisciplinary field that combines major studies of both robots and human in diverse fields such as basically HRI, artificial intelligence (AI), human-computer interaction (HCI), pattern recognition, control systems, electronics, mechanics, psychology, behavior expression systems, emotional communication, and neuroscience (Goodrich and Schultz, 2007; Murphy et al., 2010). In HRI studies, researchers usually design a robot to interact with the environment or an object, and they develop a motion strategy for a particular case (depending on the physical properties) without considering the motivation or stream of consciousness that characterize human behavior (Argall and Billard, 2010; Fong et al., 2003). In our research, in contrast, we have attempted to develop a method with which a robot can recognize the facial expressions of humans and demonstrate its own emotional expressions, depending on its 'motivation' based on a 'consciousness' system.

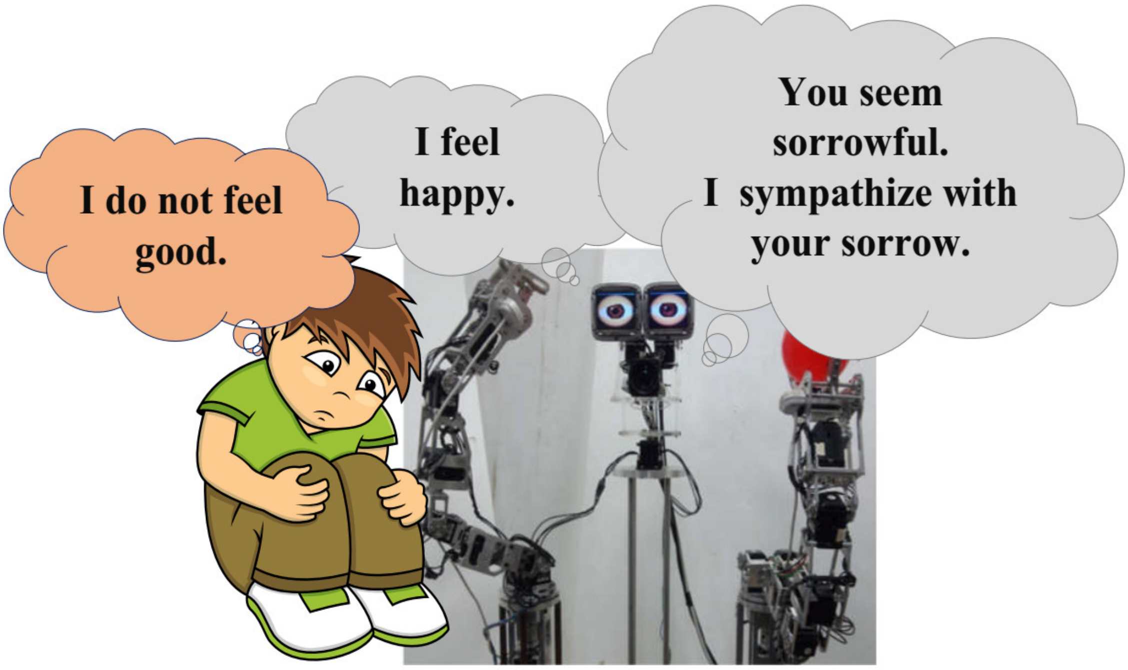


Fig. 1-2 The proposed concept of a 'companion robot' based on personal-emotional intelligence that the robot expresses the emotion of eyes by sharing emotional expression from a user.

Regarding the concept of emotional intelligence (EI), our proposed robot is also designed to consider the social etiquette that humans use for emotional expressions. To illustrate, if you are happy while your friends around you are feeling sad, when you recognize your friends' sadness you might deliberately express an emotion other happiness because relationship conflict might develop if you express an emotion opposite that of your friends'. You might show neutrality or pretend to be sad in order to share your friends' feeling and express sympathy in order to maintain the relationship. In effect, you alter your facial expression and demeanor to maintain user relationships. A robot should thus have similar skill such empathy, sympathy, that the topic is the primary focus of this thesis. This perspective view is shown in Fig. 1-2 which exhibits the robot feels pleasure on the other hand its friend feels sorrow then the robot should deliberate the expressional emotion. After the robot already select emotion following its emotional intelligence then the robot express sharing emotion as sorrow and sympathize.

The behavior of robot is complicated for human-communication if we would like to complete the system to have the cognitive in the human level since the human is the sophisticated animal that has complex mind and biology comparing with other animal (Thao et al., 1986). Therefore, the proposed system was designed with a multi-agent system (MAS) which comprises multiple interacting intelligent agents (IAs). MAS is also the main role in persoanl robots because MAS includes individual autonomous agents that can be a participant observing environmental states, the learning state, or the action state relating the cognitive process, which can also include sub-state depending on the complexity of the system (Byrski et al., 2015; Panait and Luke, 2005). We also utilize the MAS aspect, which is the perception state, consciousness state, action, and expression state, which we describe in the next chapter. In this research, we launch the system of conscious behavior decision as an agent using the biologically inspired topological adaptive resonance theory (TopoART) which the method is the fast-online learning, robust and stable for noisy data. TopoART improves the ART by using topology learning with the addition of sub-networks at different levels of detail (Tscherepanow, 2011). Therefore, this method is more suitable for real-world information. The machine learning of great biologically inspired networks also includes those such as Self-Organizing Map (SOM) (Kohonen, 1982) and Perceptron (Rosenblatt, 1958), however, SOM and Perceptron are quite wide of the real-world information because that is sensitive to noisy information and not an on-line learning.

Due to humans being social animals that have to communicate with each other, the robot must have the skill of the ability to perceive and understand the emotional expression of itself and from others surrounding it, which is regarded as emotional intelligence (EI) skills or social intelligence (SI). We highlight this by implementing and demonstrating the new reorganized EI state with this research framework to the robot, which is the great benefit of this system. Consequently, the robot could be a socially autonomous agent as an intelligent companion for a human. For the first gate of emotional expression, which is a capability of empathy for human expression, we usually express our feeling by first the face then body and mannerisms. The robot therefore expresses its feeling by its face because that is easy to comprehend for humans. Facial expression is a fundamental expression of human emotion driven and conditionally followed by a neurological mechanism and by moving muscles beneath the skin according on the formation of a cortical route in the brain (Rinn, 1984). It is also difficult to conceal the feeling inside an emotion. The robot system should therefore understand the facial expression of the user.

Many studies on facial expression recognition (FER) have attempted to classify emotion. These methods necessarily implement the recognition algorithm together with some machine learning algorithms. Support vector machines (SVMs) are a popular way of analyzing data and recognizing patterns for classification (Cortes and Vapnik, 1995). Other methods include hidden Markov models (HMMs) (Rabiner, 1989) and principal component analysis (Abdi and Williams, 2010). To implement a FER system, we must first implement facial feature extraction, for the recent methods which have been proposed; such as, the active shape model (ASM) (Cootes et al., 1995), the active appearance model (AAM) (Cootes et al., 2001) and the constrained local model (CLM) (Cristinacce and Cootes, 2008, 2006). These fitting feature models were also implemented within the medical research area to classify better and fit autonomously the feature region of X-ray images. One application of the research on ASM, AAM and CLM is presented by van Ginneken et al. (Van Ginneken et al., 2002), who developed an ASM with optimal features for medical image segmentation. These methods are currently being considered for building up into the personal robot and emotional generating system.

The traditional robots slightly apply for the system without the consideration of nature cognitive of the animal to build up the robot. Consequently, the robot would not have an intrinsic movement strategy or self-motivation. Therefore, the robot cannot communicate with humans properly. Due to the cognitive process being different, the robot and human cannot understand each other's insight. McCarthy therefore proposed the idea, which is the need for a robot to have its instinct, which is the humanity that has a consciousness process, emotions, cravings, philosophy and introspection knowledge that the artificial agent can perform its behavior in the common-creature nature (McCarthy, 1995). For this reason, it is crucial that the robot's behavior embody the consciousness for being a medium agent of two terminuses that are a logic system in cognitive without behavior and behavior without representation. This aspect was described by Tran Duc Thao. Suppose a lower level animal would have a simple behavior and the upper level, which has more cells, would have behavior that is more complex (Thao et al., 1986). The emotion is additionally important to exist for the creature. For example, in self-defense, when we encounter a dangerous situation, we then feel fear that works to remind ourselves of situations we should avoid.

Therefore, we have been attempting to investigate the research according to the personal robot that can perform its behavior along with emotional expression convinced by the robot motivation and synthetic neurotransmitter, during which the robot recognizes the surrounding attended object. The robot neurotransmitter is performed by adding synthetic dopamine relating to the human brain, which is a model for arousing motivation and driving its behavior included the expression. The individual behavior embodiment of the robot is built up leaning on the organism naturalness, which can make the robot perform a natural decision and its native posture. Hence, we have designed a biologically inspired robot, which has consciousness and behavior robot, named by “CONBE robot” that can express its emotion and perform its role depending on its consciousness and motivation. This robot is built up corresponding to a semi-humanoid architecture, which includes two arms and one face.

With the thesis objective, we propose the framework of the biologically inspired CONBE robot based on the animal robot that is to enable the animal robot can perform the natural interaction with human respecting feeling sympathy and empathy. Because when the robot does not have empathy function, the robot cannot comprehend the feeling of human as well as if the robot does not have sympathy function then it cannot express the proper expression in case such as when the human feels different the robot. This major system proposes the cross emotional expression from the pet robot to human and cross facial emotional expression perception. Additionally, the robot’s expression would interact with the user using the consideration by robot’s emotion and user’s expression. The interaction uses the face of the robot to express its emotion or in the case of a manner in human society that the robot would appropriately express the facial emotion according to the social interaction and constructive engagement. Hence, the user might get more interested in the robot. For simplifier comprehension of the robot that could have a mind function such a consciousness, we then describe in the next explanation.

1.2 Background of Animal Consciousness and Mind Knowledge

Accordingly, the common problem probably deliberates formerly working out a technical solution to how we can give a robot consciousness. For the information of knowledge of the awareness or consciousness, there are two perspectives regarding this puzzle question. The first perspective is the internal reflection of the consciousness of possession; in other terms, this aspect includes my internal description of myself, such as that is conscious of an object, another, or myself. Husserlian phenomenology developed a rigorous, introspective methodology and grounded its discipline on this viewpoint (Husserl and Strasser, 1950). The second viewpoint is an objective view of the Other's "consciousness" from my viewpoint. This perspective is based on my belief that the other has such and such consciousness, an idea that the other seems aware of an object. This point of view includes interpretations of all attributes such as the Other's speech and behavior that belong to the other. Similarly, still impossible to exactingly prove, the second perspective connect to the first view due to that the other one's consciousness exists in the same fashion that one's mine does. Therefore, the existence of the other one's consciousness belongs to this notion. At this point, a humanoid robot, a "virtual human", and an artificial animal, theoretically share a common position concerning the real human other. Such an artificial creature can make a user believe that it has "consciousness" if any of its external qualities, in function and structure, are designed to make sense to a user. Structural approximation of a robot to a human normally depends on material technologies. However, its functional design can be independent of the material and structure if a digital computer is used for building robot behavior. Thus, this philosophically justifies the assumption that any artificial intelligence embedded in an artificial creature should be at least functionally analogous to a human.

Artificial Intelligence (AI) is an objective view of the logical functions of human consciousness. It is not, however, possible for AI to control behavior in an unstructured environment because not all-behavioral knowledge about an environment can be embedded in the knowledge base in advance. That is, traditional AI, such as a production system, can never ascertain the final solution of a Frame Problem, a problem in which subsidiary problems whose number exponentially increases must be solved in order to solve the initial problem. A human also may encounter a Frame Problem without the default knowledge necessary to solve a given problem. However, in that case, the human intelligence may stop tackling the problem halfway, the body responds, leaves the scene, and the person ignores the problem. This difference between the human intelligence and AI can be recognized as due to human corporeality while AI itself has neither a body nor the knowledge a body acts with. A human body is ready to react to the environment whether or not the process of intelligent continues, and conversely, human intelligence works when behavior is stopped. Even a robot that has a body can have no embodiment unless the interaction between body and intelligence is embedded as such. In contrast to AI, Subsumption Architecture (SSA), a behavior-based architecture proposed for a mobile robot (Brooks, 1991), employs neither high-level, centrally goal-oriented, nor symbolic algorithms but embeds several fixed reactive behavior modules loosely connected to each other. This architecture brings into focus what is embodied while ignoring what is in the embodiment. This structure expects the emergence of meaningful behavior from a simultaneous execution of these behavior modules. This architecture is namely by a non-Cartesian machine in the concept that it has no fundamental program similar to a human ego or consciousness to control behavior. However, there was a diversity of models regarding mind, with concepts between the two extremes of AI and SSA, to code computers to mimic artificial creatures, for instance (Koenig, 2000). Linkage of intelligence and behavior is necessary to mediate between the two extremes: a logic system, rigid or fuzzy, without behavior and behavior without symbolic representation. For this linkage in modeling consciousness, that should be taken into consideration concerning when a human recognizes the meaning of a behavior obstruction as the cause of obstruction, the definition of a behavior obstruction to a lower level animal is given an emotional value, positive or negative. Then, in animals, consciousness can be linked to behavior in the sense that consciousness embodies the meaning of obstructed behavior reified in the body. In this thesis, we designed a software architecture, Consciousness-based Architecture (CBA) with an evolutionary hierarchy between consciousness and behavior to link animal-like reactive behaviors with symbolic behaviors. The feasibility of the architecture was tested by computer simulation of behaviors including sleep, reflex action, approach, and detour. Since this work, we have designed behavior selection of criteria based on the environmental meaning as two-valued, positive and negative, emotions. With these criteria integrated into CBA, experiments using two robots loaded with this architecture successfully demonstrated ambush to capture prey. The present research demonstrates the relationship between CBA and human consciousness and behavior.

For the aspect of the organism consciousness belonging to Husserlian phenomenology proposed, human consciousness is the feedback process of giving meaning to an object (Husserl and Strasser, 1950). By the Husserlian proposition, the author assumes from a more technical rather than the philosophical viewpoint, that the consciousness process has the following nine characteristics:

- First-person perspective: without the use of the first person, the self, nobody can describe what he/she is conscious of.

- Feedback process: we come back to know the abstract attribute, meaning, of an associating object in its totality in a thoughtful manner. This method does not process in only a linear one however a feedback method of reduction: we repeatedly shift our attention from a particular concrete property of an object to its abstract attribute until we directly see the essence of an object and its connection to the core of other beings.
- Intentionality: a mental phenomenon that directs itself toward an object, internal or external.
- Anticipation: For the reflective process of perception task of objects, then anticipation of what will carry out as a meaning of the object develops as the object identification proceeds further. Anticipation perform an major role in controlling this process: the anticipation is a reference from which different types of meaning of the object are discarded. Unless the anticipation is disappointed, it becomes a belief about information of the abstract property of the object.
- Embodiment: we can be conscious of having corporeality in the external world and that the body is at our disposal. Only two types of events bring body consciousness to us. The first one is perception, and the second is obstruction of body action.
- Certainty: we see the meaning of an object with some degree of certainty at each step in the feedback process of understanding,
- Otherness: We believe that other individuals have thoughts and feelings, i.e., a mental life, and that it resembles our own.
- Emotionality: consciousness can be emotional. There are two sources of emotion: the first one is perception, and the second is corporeality.

- Chaotic performance: the intentionality and the reflex process of recognition or perception of an object are disturbed by randomly generated mental events. If someone is thinking about something, other things outside the context abruptly rise in my mind, and some of them remain to change the flow of the original meaning until the flow of consciousness returns to the initial one.

As the knowledge and information that we rest the explanationม, source information, the problem and hypothesis. The next will explain the problem statement of this research that we aim to achieve the objective because in that solution there would be the light of an ability of the future robot that can improve the personal robot or social robot further.

1.3 Problem Statement

According to the robot trend in the future and the needed technology for the application, the robot in the non-industrial area encounter against the difficulties of the instinct motion process which is nature of animal that encompass the recognition, comprehension, and motor driving action. Since the traditional normally perform following the human instruction however if the robot can perform with it natural physical or biology process relating to human, the robot should have the self-nature behavior and cognitive process as same as animal. Accordingly, without considering the instinct action that produce by the consciousness and the emotional communication the robot will perform similar, as the human imitating without the soul or the natural action which has in creature depending on each spicy for example the cat has own action and kinematic motion as well as the dog also has own action and kinematic motion. Consequently, the robot cannot be attractive to user because it does not have own nature behavior and motivation as well as consciousness structure. This research then proposed the system to address the problem by initiating the Consciousness-Based Architecture (CBA) and emotional intelligence system based on the aspect of combination between mind and brain-biology to make robot behavior intuitive but from the conventional CBA has a restriction because the behavior could only perform depending on the constrained level from human instruction or program. On the real-world system, there are not the permanent rules for selecting the action because of the complication of cognition and behavior system of animal. Thus, we implement the CBA with the online brain-inspired method respecting to a human being, with using the artificial neural network for autonomous learning and learning for real-world data as well as the affective motivation to perform the robot behavior and feeling. The affective and behavioral system would determine the relationship between affection and action correspondingly. Finally, all issues would be addressed by the proposed along with demonstration.

1.4 Research Purpose

The general objective of this research project is to create the behavioral - emotional expression system for Conbe robot to enhance intelligent behavior and emotions, and to facilitate communication between users and robot. We seek to increase the robot's behavioral-emotional intelligence capabilities so that the robot can distinguish, adapt and react to changes in the environment. After investigation of the literature of previous researches done about the behavior selection, and emotional expression models based on an artificial intelligence neural network. We design the robot framework with proposed system to fulfill the function of the robot, which is mentioned.

Our objective of the proposed research is to develop the behavioral robot which act instinctually likes an animal being and can communicate to human without the confliction. We then develop the robot implemented with affective and behavior system for operation of the instinct behavior. In addition, for coexisting with human, the robot is necessary to have ability of the emotional intelligence because this skillful is important for the communication between human and robot without conflict.

From the conventional work, the robot in our work could perform the six emotions based on the basic consciousness level (explain in chapter 3). The robot can express the emotion by the limitation from the human instruction depending on the object. For example, when the robot recognize the like object the robot emotion would become pleasure depending on increasing motivation. That means the robot map one object to one emotion. In this thesis, we improve the adaptive emotional system not only the robot map the emotion to object, however that also depending on the context around the robot. The context in this condition means the surrounding people around the robot that can also induce or adapt the robot emotion depending human expression. For example, instantly, the robot is fear but the user is pleasure then the robot is influenced from user and probably express the neutral or hope expression instead of its fear.

In order to archive and approach to the organisms being of emotional expression, the robot should performs ability of the emotion understanding to the user, we have developed a system that facial expressions on the basis of the two emotions of the user and the robot.

- To investigate and study on the personal robot which can make a possibility to co-existing with human in real life and seeking for the necessary capability, which the service robot should be able to perform.
- To initiate the robot behavior and consciousness process relating to the animal being that based on the aspect of combination of mind and brain inspired.
- To implement the cognitive model based on the consciousness based architecture combining with the brain-inspired method, which encompass the affective system and behavior system generating.
- To perform and demonstrate the robot capability of the intelligent behavior and emotional intelligence with user that is to proof the robot performance and affinity with user.

1.5 Overview of the Thesis

According to present and explain the detail of the proposed work, the dissertation was organized into six chapters that include the behavioral model, emotional model, emotional intelligence, methodology, experiments and conclusion. The rested chapters are the explanation as follows.

Chapter 2 presents the system organization of the CONBE robot that comprise the overview organization, hardware and software system configuration, connection and communication of system and behavioral motion control.

Chapter 3 elucidates the related theory for the research system for the pet robot. The contents are composed of Hidden Markov Model, Constrained Local Model and Topological Adaptive Resonance Theory. Those are the basis elements of the robot system.

Chapter 4 explain the methodology to clarify the system process about the cognitive behavior that based on the consciousness based architecture. Moreover, the primary essence point also contain in the chapter that are the methodology of affective system which is the inside state of the robot as same as human. The human has the private state or private part that does not aim anyone to come in his mind. In addition, by implement with affective inside state that should rest the robot can have more the consciousness lever and more complex behavior respecting to the nature animal or human.

Chapter 5 then we demonstrate the experiment to show the performance of the robot along with inside state and emotional interaction skill based on the emotional intelligence which mainly proposed of this research.

Finally, chapter 6 describes the summarized conclusion along with discussion. In addition, there is some suggestion for the future work to make a robot getting more intelligence that can perform interacting in the real world situation.

Chapter 2

Configuration of CONBE Robot System

In this chapter, the configuration of the robot is described according the robot construction, which is composed of the hardware configuration, software organization, the structure of communication, and the control of posture expression that is based on the CONBE robot. Consequently, we present the detail of each section about the subsystem that contains the method of configuration and performance such robot design, hardware part and information, construction process, robot function in the action and appearance view. Finally, the posture system of behavioral robot is elucidated in the detail of each action that the robot can operate and interact with the user.

2.1 Overview of the System

This section presents the robot construction and system respecting to the arm robot. Fig. 2-1 left shows CAD design of the CONBE robot that appearance relates to human in upper-body (left) or semi-humanoid robot, on the right, system configuration diagram of connection in the robot is shown. Additionally in the figure shows the block diagram of the arm robot, which the system is constructed from the six-degree-of-freedom actuators, a small web camera that is used for the robot vision, a two-degree-of-freedom of robot head, CCD camera, and a personal computer, which is the centralized control system using Windows platform. We use the motors based on ROBOTIS Company by Dynamixel DX-117 platform operating as the actuator that are installed into the robot arm and the head of robot (“DX-117,” n.d.). The actuators are connected with the computer by USB cable. Additionally, for the vision, the web camera is embedded on the palm of the robot arm that also connects by USB cable to the PC.

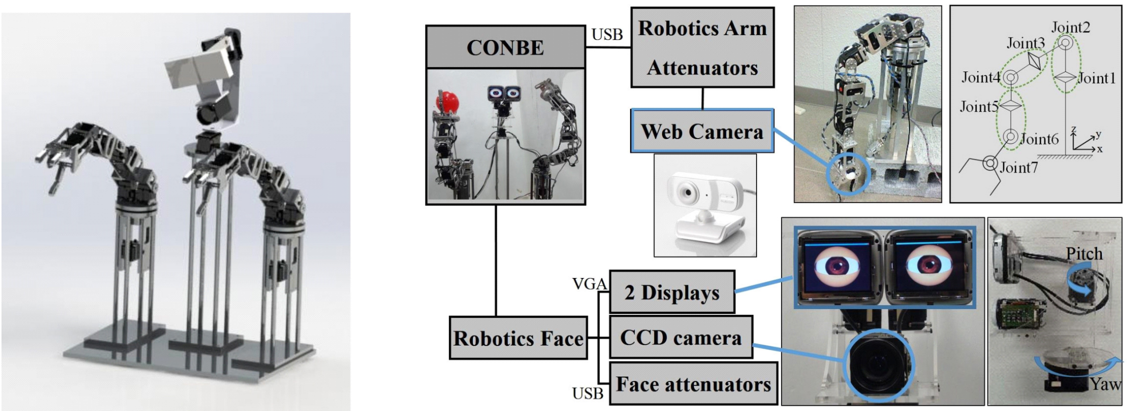


Fig. 2-1 The CAD design of the Conscious and behavior (CONBE) robot that appearance relating to human in upper-body (left), System configuration diagram of connection in the robot (right).

2.2 Robot Construction Overview

According to animal-like behavior "CONBE" robot, the robot is employed to perform the animal or pet behavior system combining cross-communication between human and robot to enhance the previous robot skill that only perform with the simple object based on the CBA in order to rest more attractive and sophisticated behavior as similar to the human being. In this section, the structure of the arm hardware including actuator, vision system and the head composition which use for affectively communicate to human, are clarified the detail of the function and composition that relating the robot action and appearance.

2.2.1 Robot Manipulator

The robot arm is the major part to behave a pet behavior to interact with the surrounding environment that is also shown in Fig. 2-1. The construction of the robot assembled by actuators. Fig. 2-2 shows the joint motion diagram of the robot arm, which encompass seven joints that each joint can rotate in one axis. For the arm dimension, we design the total length of 450 mm. The arm robot is designed respecting to the joint of human arm by joint 1 and 2 represented as shoulder, joint 3 and 4 represented as elbow, joint 5 and 6 represented as wrist. For the hand part, joint seven is designed with a three-finger by single degree-of-freedom actuator. The weight of the robot arm is approximately one Kilogram. The hardware dimension of the arm robot is shown in Fig. 2-3, which is divide into three parts of shoulder, elbow, and wrist that the length of each part is 150 mm. In additional, the actuator has the function to monitor the temperature of actuator because it is important when the load is high, the temperature will significantly increase. Therefore, we can prevent the damage of actuator. Notice, for the shoulder part at the joint two, we use two actuators because the high load at the base position that has to undertake the remaining actuators. We install two actuators complementary each other to avoid the overload of actuator. As we described, all actuator is adopted on the Dynamixel DX-117 platform of ROBOTIS Company, the detail of the communication and control will be present to the following part.

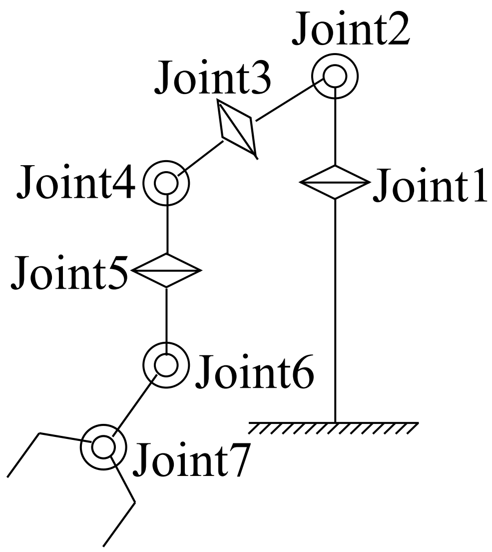


Fig. 2-2 The motion diagram of the robot arm which encompass seven joints that each joint can rotate in one axis and assembled by actuator DX-117.

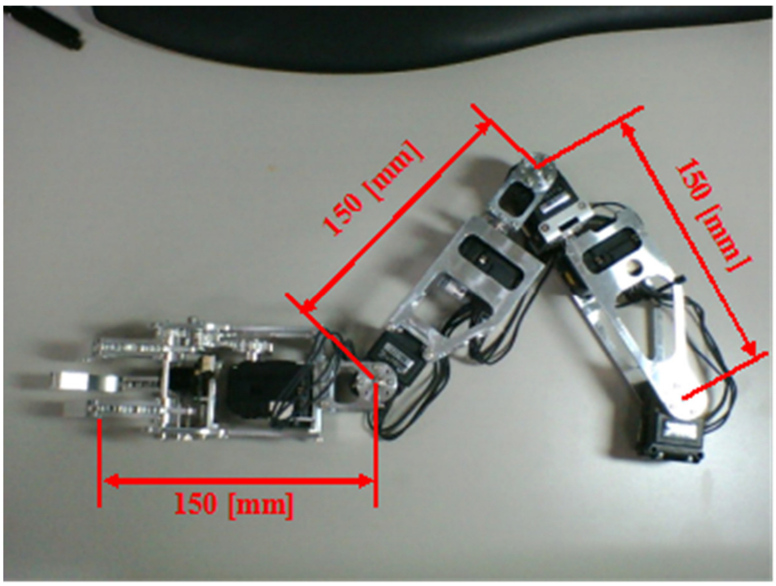


Fig. 2-3 The divided part relating by three parts of shoulder, elbow, and wrist.

2.2.2 Actuators

This section describe the detail of actuators, which we utilize for mechanical element of the robot as a joint movement control. We use the Dynamixel actuators, which are high performance networked actuators, installed with gear head mechanism, the close-loop position and velocity controller system, and the serial RS-485 control communication. Moreover, the actuator also has a versatile expansion capability, powerful feedback functions, position, speed, internal temperature, input voltage, etc. it can communicate simply daisy-chain topology for simplified wiring connections in case of multi actuators.

Table 2-1. The specifications of Dynamixel DX-117 actuator

Weight	66 g
Dimension	31 mm x 46 mm x 37 mm
Resolution	0.29°
Gear Reduction Ratio	192.6 : 1
Stall Torque	3.7 N·m (at 18.5 V, 1.9 A)
No load speed	85 rpm (at 18.5 V)
Running Degree	0° ~ 300°
Running Temperature	-5°C ~ +80°C
Voltage	12 V ~ 18.5 V (Recommended Voltage : 14.8 V)
Link (Physical)	RS-485 Multi Drop (daisy chain type connector)
ID actuator	254 ID (0~253)
Communication Speed	7343 bps ~ 1 Mbps
Types of Feedback	Position, Temperature, Load, Input voltage, etc.
Material	Full Metal Gear, Engineering Plastic Body

For the data transfer between PC and motor, the actuators use a serial RS485 as a bus communication to connect each device. The device is able to use the speed up to 1 Mbps. Because of the bus communication, it is simpler to construct the device with the wiring. The motor is showed the appearance of the actuator in the overview figure of the robot above. The particular specification of the actuator is shown in Table 2-1, which the major functions such as the maximum resolution from 0 - 1024, the rotational angle from 0 – 300, and maximum torque up to 3.7 N·m.

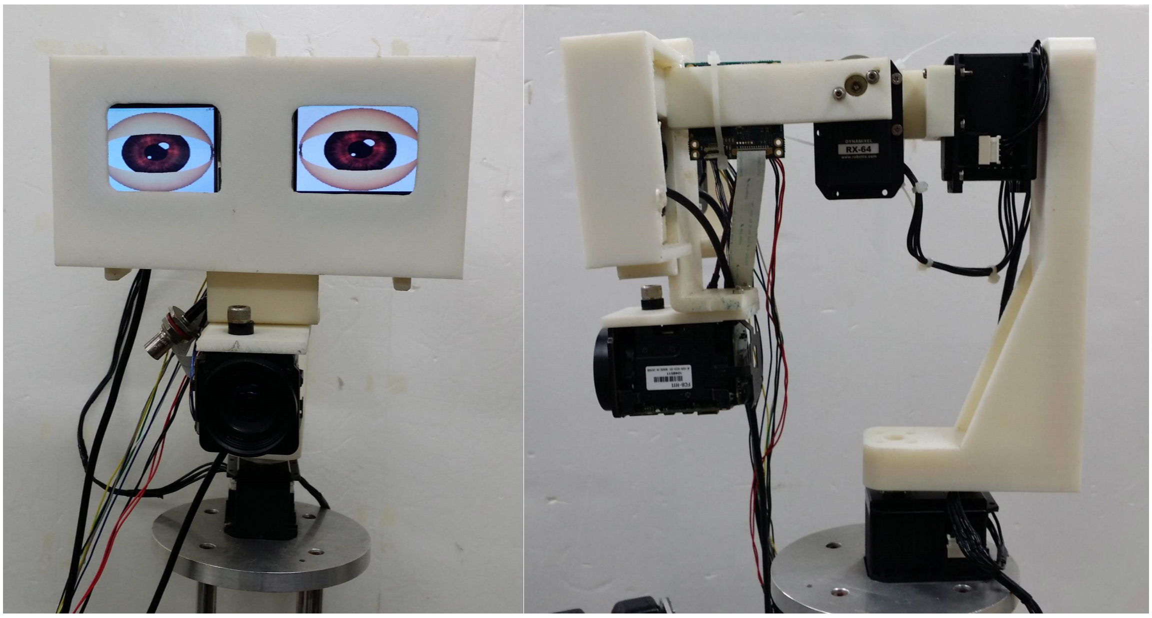
2.2.3 Web Camera

A web camera is used for the vision of the robot, which the camera platform is UCAM-DLV300TWH mouthed on the robot hand that the camera appearance is also presented in the overview figure of the arm robot at Fig. 2-1. This camera is compact size with the dimension of W69.5 × D20 × H52 mm. The number of the maximum resolution is 300 million pixel that the maximum size of the image is 2048 × 1536 pixel. The device is also compatible to connect with USB communication to PC.

2.2.4 Robot Head

Regarding to the cross-communication between robot and human, CONBE robot is used the facial expression to be the major interaction. For the head robot movement, there are two degree of freedom. For the actuators in the robot’s head, CONBE head equip with Dynamixel RX-64 actuators are used to be yaw and pitch movements. With the RX-64 servo actuator is one of ROBOTIS most powerful smart actuator that is similar to DX-117 however it can use higher tourqe and load. It can provide a 888 oz*in of torque at 18 VDC, and it can traverse its entire 300° range in under 1 second. Each servo motor has the ability to track its speed, temperature, shaft position, voltage, and load. All of the sensor management and position control is handled by the servo motor’s built-in microcontroller.

In the head section, the robot also installed with industrial embedded camera by SONY Company, which is FCB-H11 module. The head can express the eyes appearance that is the 3D virtual eyes designed following human eyes using LCD small monitor. The dimension of the head is W150 × D150 × H200 mm. the camera in the head is used to identity the person and for the facial expression recognition. For the communication of the devices, the camera and the actuator are used with serial RS232 communication, small LCD monitor used by USB video composite converter. The overview of the robot head hardware with front and side view are shown in Fig. 2-4, the illustration of CCD camera and communication interface platform is also shown in Fig. 2-1.



A) Front view B) Side view

Fig. 2-4 The overview of the robot head.

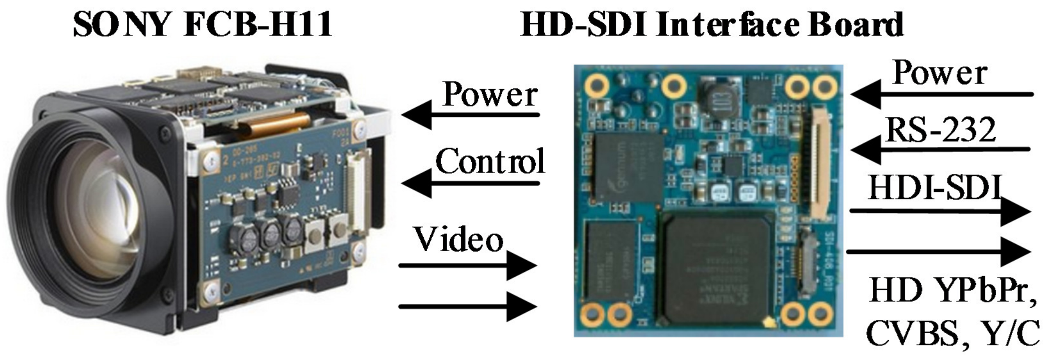


Fig. 2-5 Connection diagram for FCB-H11 camera

2.3 Software Organization

In this section, we describe the software system, which is programmed and installed in the PC based on Windows Platform. The software is developed by Borland Builder C++ software. The detail of each part will present in the next following.

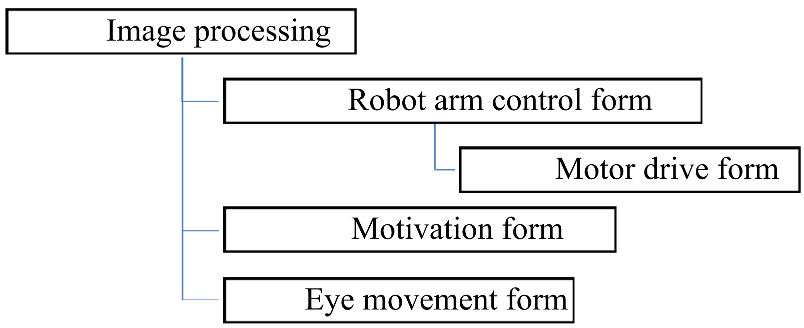


Fig. 2-6 Software system diagram.

2.3.1 Hierarchy of the Control Program

In the control system of the robot arm, we organize the software dividing into window forms by the distinction of the operation due to simplifying management. The windows form include a motor drive form for driving the motor; the robot arm control form which performs posture control and motion of the robot arm that also operate together with a motor drive form; the image processing form is to determine the orientation of target position of the interesting object obtaining from the image by the web camera; and motivation form perform the occurring calculation of the motivation and dopamine of the robot. Finally, the eye movement form is used to show the robot appearance of the expression. The software diagram is built dividing in five models that were layered as Fig. 2-6.

2.3.2 The Window Form of Motor Drive Control

Concerning the posture of robot arm, the actuators or motors is the basis component to control the arm movement. As mention above in section 2.2.2, the actuator Dynamixel DX-117 is used in the CONBE robot that can freely control the function of actuator such the target angle, driving speed, compliance. The motor control form was developed in the conventional study. However, this research has also customized some function to improve the capability of the motor. This section describes the instructions control that mainly use in the arm control of position and posture. Let give an example command below.

The following instruction command is the main command to adjust the set of the parameters such as motor speed control, position control. Moreover, the next explanation describes the function and usage for each command used in the robot arm system as following.

“put_commandi(command, id, value, msg)”

With respect to above command pattern, the following command is to provide and access a set of parameter for an instance function.

“motor_setting_modification(Mod_case, MotorID, Parameter)”

Given example according following command below, this command is used to set the speed of the motor ID 0 as 10 percent that means slow down.

“motor_setting_modification(s , 0 , 10)”

Moreover according to following command below, this command is used to set the compliance slope characteristic of the motor control to prevent the abrupt movement. The command is applied to the motor ID 6.

“motor_setting_modification(c , 6 , 100)”

The two following commands are used to specify the target angle of the actuator that use when sending the actual driving instruction while the arm moving.

“put_commandd(command, id, value, msg)”

“put_command0(command, id, msg)”

In additional, in some case, it is not necessary for getting the acknowledgement from the motor, we can skip the beginning command such as following.

“put_commandi(command, id, value, msg)”

“put_commandd(command, id, value, msg)”

“put_command0(command, id, msg)”

2.3.3 The Windows Form of Robot Arm Control

With the windows form of the robot arm, it is applied for performing the posture control of the robot arm. The GUI of windows form is shown Fig. 2-7. In this form, there are 8 major parts in GUI form, which the first part is for serial communication port opening and closing of motor connection. The second part is manual control part, which can control for increasing or decreasing the motor angle for 10 degree at a time. The third part is applied to display the current angle and the target angle of each motor.

The forth part is composed of three sub part which the top part is implemented to show the hand coordinate determined by forward kinematics. The middle part is to display the target point that determine by the vision system using web camera and calculation the orientation of the arm posture. The below part is used display the camera view. For the fifth part, that is for manual control arm movement according to autonomous control hand position in Cartesian coordinate. The sixth part is used to control the mode movement of the arm that the mode is composed of autonomous behavior, semi-autonomous behavior and manual control which is regarding to the seventh part. If three button are OFF, the arm movement control is depending on the second part. For the Eight part, all buttons are regarding to the behavioral category of the robot action that we can control the posture by clicking the button.

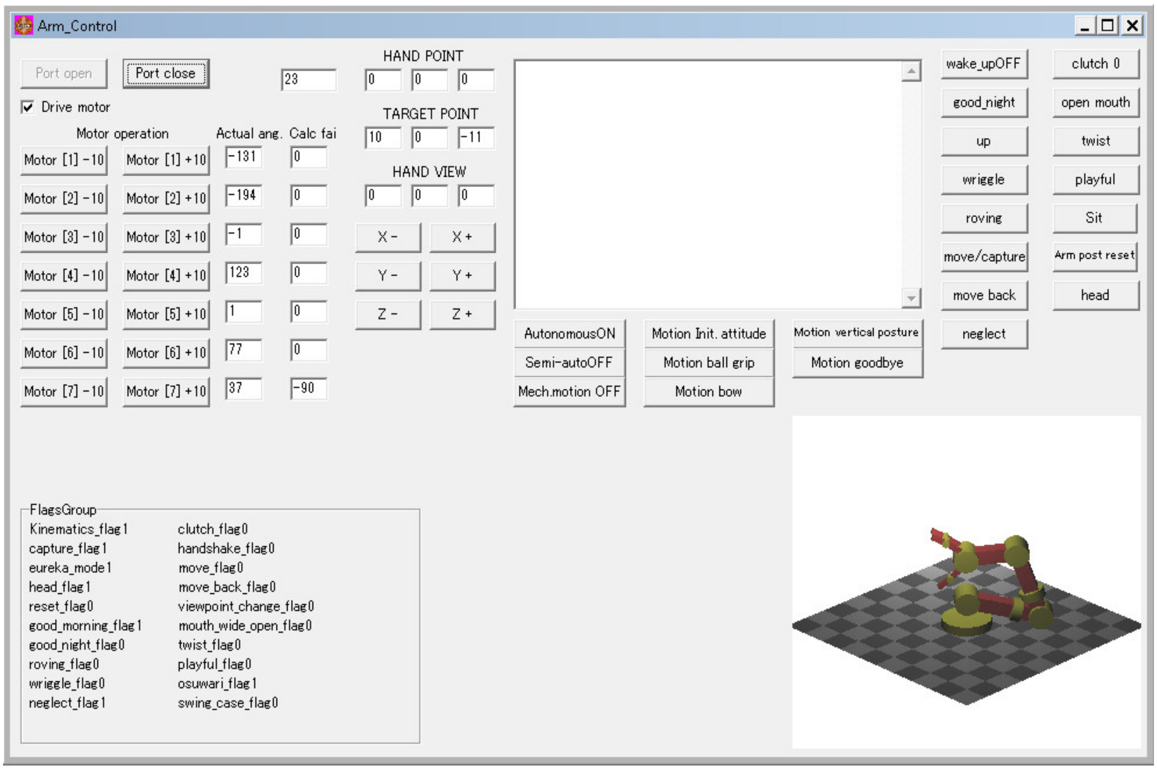


Fig. 2-7 Windows form of the robot arm control

2.3.4 The Window Form of Image Procession System

The image processing form is performed about the image analysis that obtain an instant image from the camera on the hand. This section is used for recognition of the external environment. We also determine the position of the interesting object because the position, size, identification of the object that will affect to the motivation and behavior afterward. The GUI of image processing model is shown in Fig. 2-8 that shows hue of the histogram of external information, and information such as the distance and the center position of the labeling objects by calculation from the number of appearance pixel. Additional internal information is also displayed the information of arm device such as the average temperature and the total amount of movement of the actuator at the time of the robot arm operation.

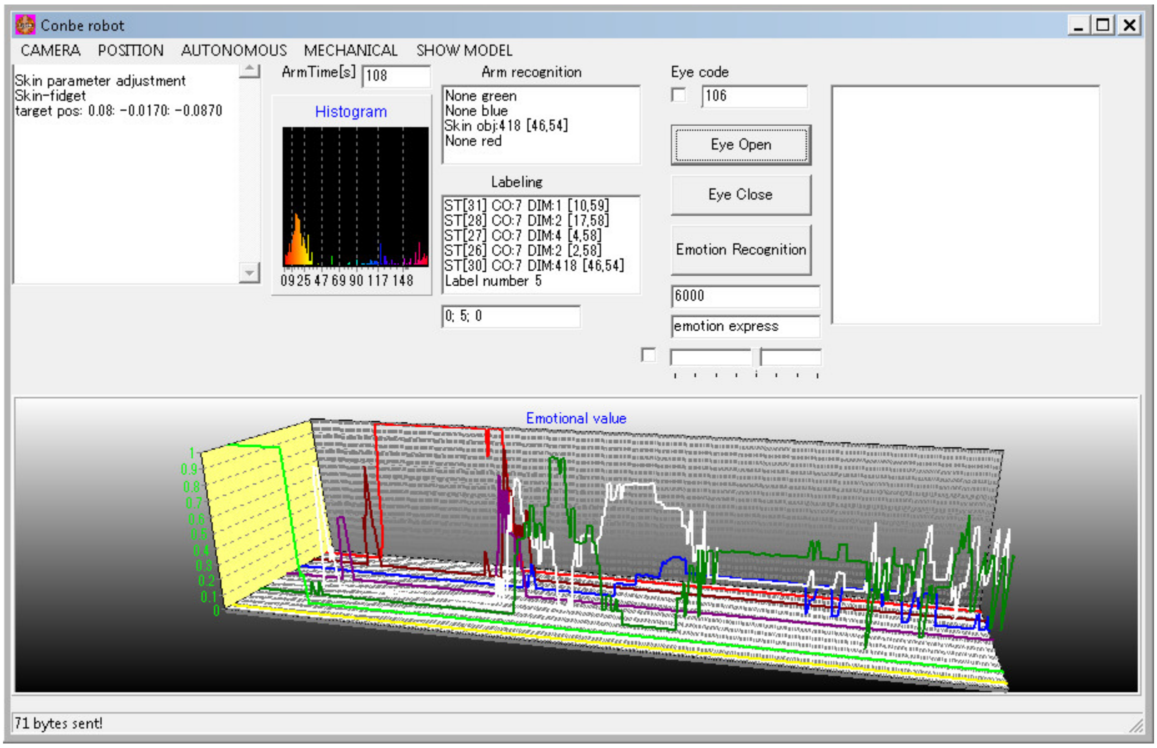


Fig. 2-8 Windows form of image processing part

2.3.5 Motivation Window Form

The motivation form is applied for monitoring about the parameters and information about the robot arm cognitive process especially the neurotransmitter and motivation system. This software part also performs the calculation of the dopamine and motivation of CONBE robot that the major part to influence the robot behavior. The windows form of motivation is shown in Fig. 2-9, which is composed of 3 part. The first on the top right of the windows, is used to start and stop the motivation determination process. The second is to display the motivation level and dopamine level depending on instant environment that they are shown as the graph plot. The third part is the assisting buttons to create the dopamine of red, green and blue object for the needed experiment in some situation.

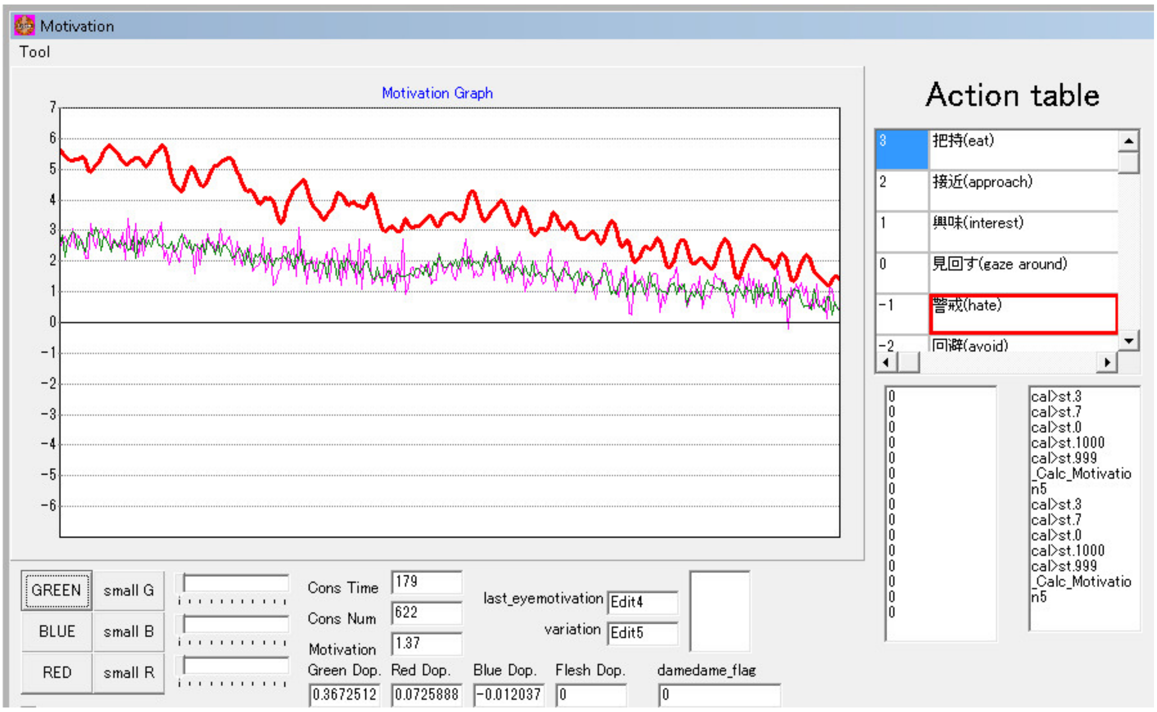


Fig. 2-9 Motivation form

2.4 Computation of the Robotic Arm Posture

Fig. 2-10 shows the robotic arm, which is divided into 4 parts: a shoulder, an elbow, a wrist and the fingers, because that is difficult to determine the angles of all joints from the target position by using inverse kinematics. Thus, in the research that uses the forward kinematics, which expresses using homogeneous coordinates and is able to calculate the posture from the joints of a shoulder to a wrist.

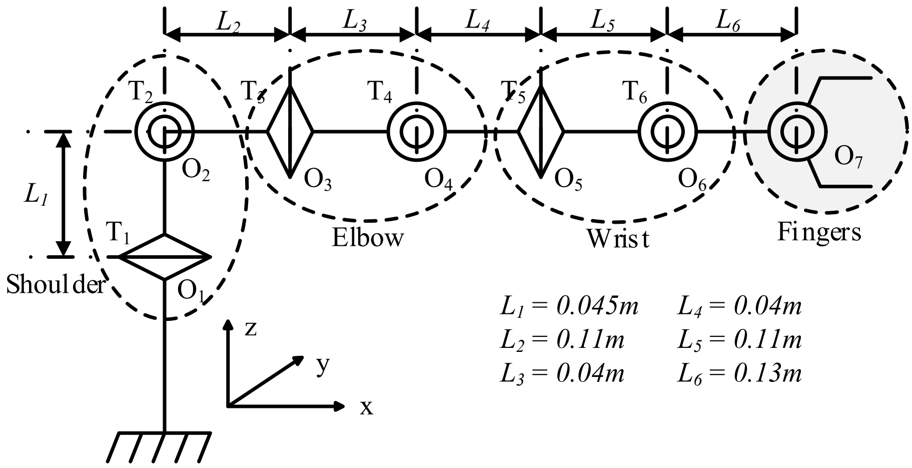


Fig. 2-10 Arrangement of degrees of freedom

2.4.1 Calculation of the Position for Each Joint

Each joint is shown in Fig. 2-10, the homogeneous transformations that described in the previous chapter is used for calculating the position of each joint, has a formation in forms of the transformation matrices or called homogenous transformations. Thus, the transformation matrices for each joint can be expressed by Equation (2-1) to Equation (2-6).

$$T_1 = \begin{bmatrix} \cos\theta_1 & -\sin\theta_1 & 0 & 0 \\ \sin\theta_1 & \cos\theta_1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2-1}$$

$$T_2 = \begin{bmatrix} \cos\theta_2 & 0 & \sin\theta_2 & L_2\cos\theta_2 \\ 0 & 1 & 0 & 0 \\ -\sin\theta_2 & 0 & \cos\theta_2 & L_2\sin\theta_2 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2-2}$$

$$T_3 = \begin{bmatrix} 1 & 0 & 0 & L_3 \\ 0 & \cos\theta_3 & -\sin\theta_3 & 0 \\ 0 & \sin\theta_3 & \cos\theta_3 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2-3}$$

$$T_4 = \begin{bmatrix} \cos\theta_4 & 0 & \sin\theta_4 & L_4\cos\theta_4 \\ 0 & 1 & 0 & 0 \\ -\sin\theta_4 & 0 & \cos\theta_4 & L_4\sin\theta_4 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2-4}$$

$$T_5 = \begin{bmatrix} 1 & 0 & 0 & L_5 \\ 0 & \cos\theta_5 & -\sin\theta_5 & 0 \\ 0 & \sin\theta_5 & \cos\theta_5 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2-5}$$

$$T_6 = \begin{bmatrix} \cos\theta_6 & 0 & \sin\theta_6 & L_6\cos\theta_6 \\ 0 & 1 & 0 & 0 \\ -\sin\theta_6 & 0 & \cos\theta_6 & L_6\sin\theta_6 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2-6}$$

where, the position vector of the first joint is P_1, the positon vector of joint i can be considered in Equation (2-7), the local coordinate system of joint is calculate by using the inverse of the transformation matrix (T^{-1}) as shown in Equation (2-8).

$$P_i = T_{i-1} \ldots T_4 \cdot T_3 \cdot T_2 \cdot T_1 \cdot P_1 \tag{2-7}$$

$$T^{-1} = \begin{bmatrix} R^{-1} & -p \\ 0 & 1 \end{bmatrix} \tag{2-8}$$

2.4.2 Methods of Posture Control

As described above, if the angle joints in the robotic arm are calculated by the inverse kinematic, that is difficult to solve the inverse kinematics problem and tend to take a long time. Therefore, in this study, the robotic arms are will be considered and determined all angle joints by dividing as the shoulder, the elbow and the wrist parts, each part that has 2 degrees of freedom. Then, the hand of the robotic arm is able to move to the target position without the inverse kinematics function. In order to create the movement patterns, the robotic arm can be divided into 3 steps according to the following sequence of step.

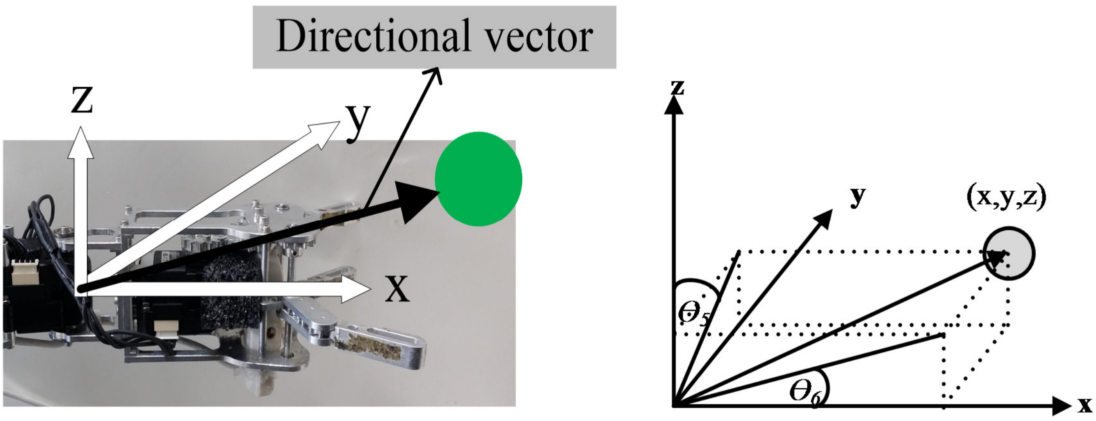


Fig. 2-11 The relationship between the robotic hand and the target position

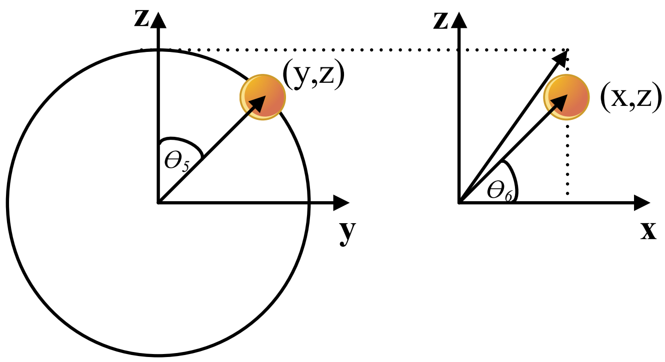


Fig. 2-12 Geometric diagram.

2.4.2.1 The wrist movement

Fig. 2-11 shows the relationship between the robotic hand and the target position. For the Fig. 2-12 illustrates Geometric diagram that can determine the local coordinates of the wrist part by Equations (2-9) and (2-10).

$$\theta_5 = \cos^{-1}\left(\frac{z}{\sqrt{y^2+z^2}}\right) \tag{2-9}$$

$$\theta_6 = \cos^{-1}\left(\frac{-x}{\sqrt{x^2+y^2+z^2}}\right) \tag{2-10}$$

By the above explanation, if there is the target object within the range of wrist movement, the robot hand can direct toward the target position at all times as shown in Fig. 2-13 (a). However, if the target position seems to be out of the range of wrist movement as illustrated in Fig. 2-13 (b), the robotic hand cannot approach to the target object, consequently the previous joints (an elbow) that are considered.

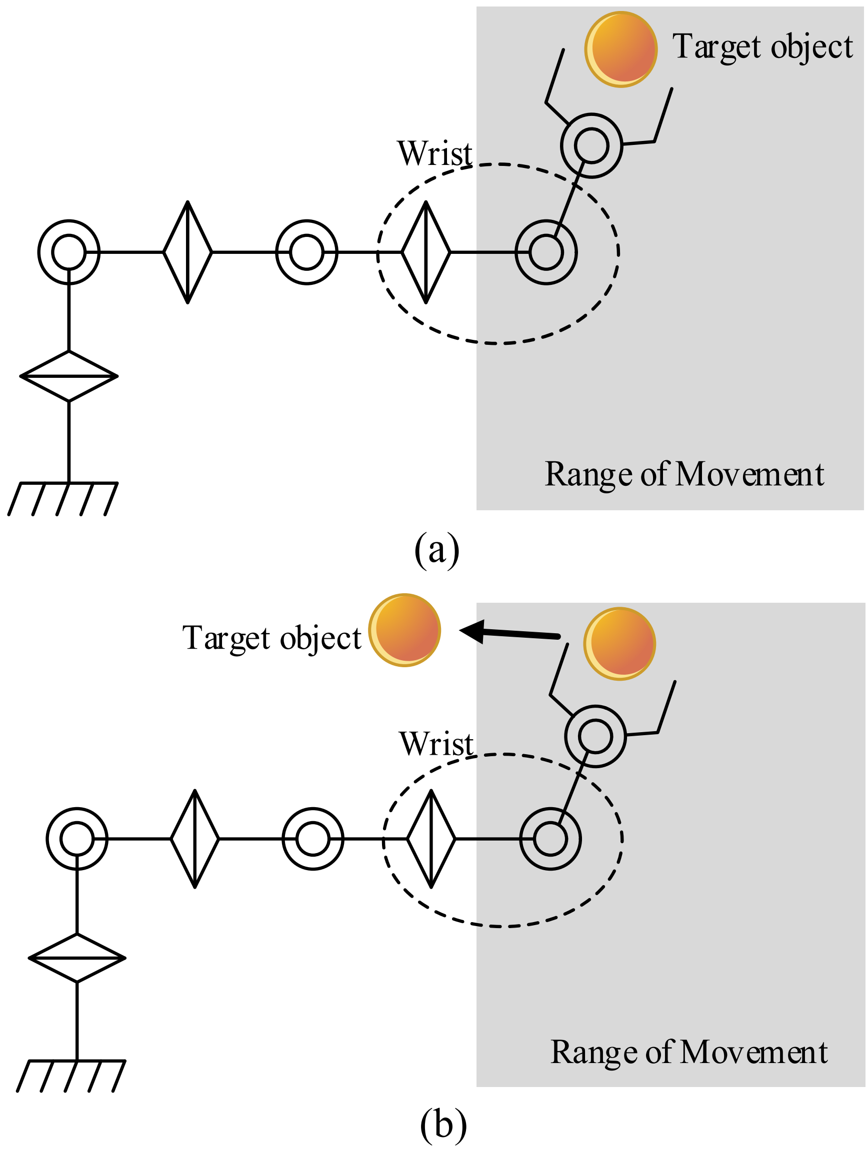


Fig. 2-13 The range of wrist movement

2.4.2.2 The elbow movement

If the target object is moved outside the operating range of the wrist movement, the robotic hand is impossible to capture the target position. The final posture is calculated using 2 DOF of the wrist part and 2 DOF of the elbow part. The elbow movement is based on pattern motions dependent on a deviation from the object, an adaptive posture can select the movement patterns based on the 9 ways of posing allowing the hand is to reach a position close to the target object. After that, the wrist movement is performed. The elbow and wrist movements are operated together as shown in Fig. 2-14.

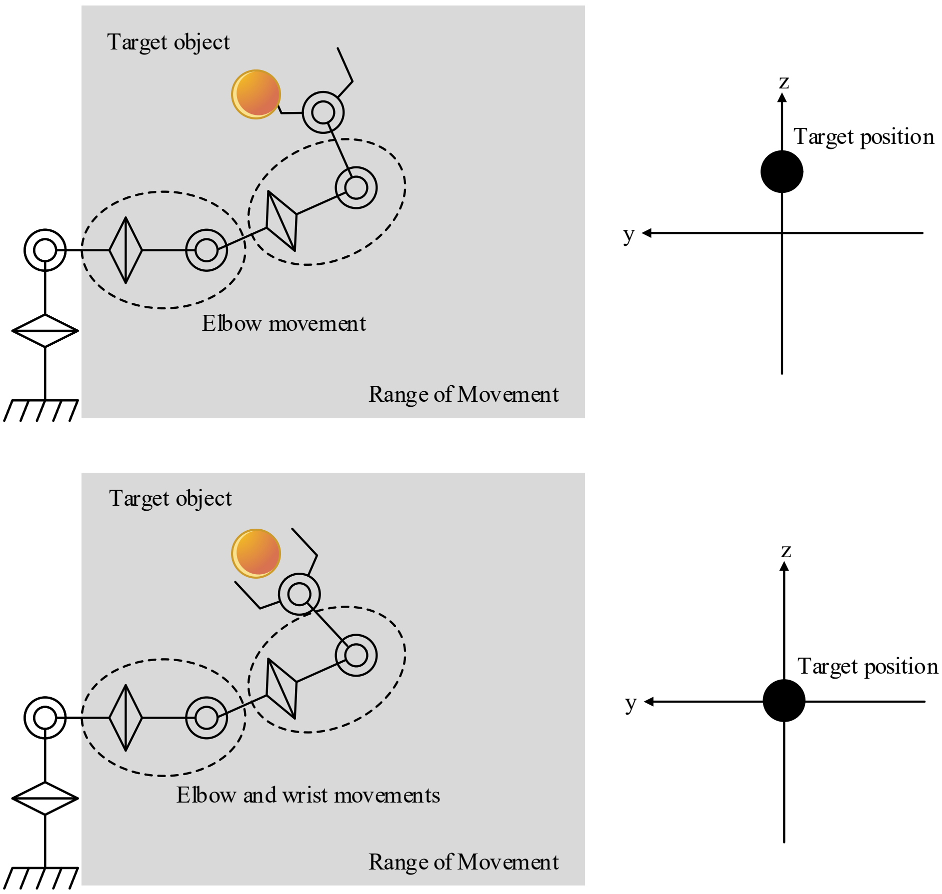


Fig. 2-14 The elbow and wrist movements

2.4.2.3 The combination of the elbow and shoulder movements

In this case, that uses two DOF of the shoulder part as a way of achieving the posture for gripping the target object. Therefore, the total of posing 81 ways is calculated, that is a combination of an elbow and a shoulder movements. In Fig. 2-15(a), Fig. 2-15(b) and Fig. 2-15(c) show the sequential movement of the robotic arm that can continuously operate the movement, and toward to the target object without inverse kinematic solution.

2.5 Summary

In this chapter, the system configuration of the CONBE robot was presented including the detail of the hardware, software, communication system. This chapter also illustrated the appearance and the function of the software that was described in detail of each form depending the function. For the small web camera on the hand, we conducted a given example of the image obtaining from camera to show how the vision system work. Moreover, we explain the actuators control function along with the parameter adjustment depending on the robot action that is possible to easily motor control as posture control. Finally, we have described the head of the robot in order to express the eye's expression and interact with human. This chapter is the fundamental of the robot system that is utilized for the proposed of the thesis. Particularly, the motivation and perception system that will apply with the system of the emotional generation with expression that is the major contribution of this thesis.

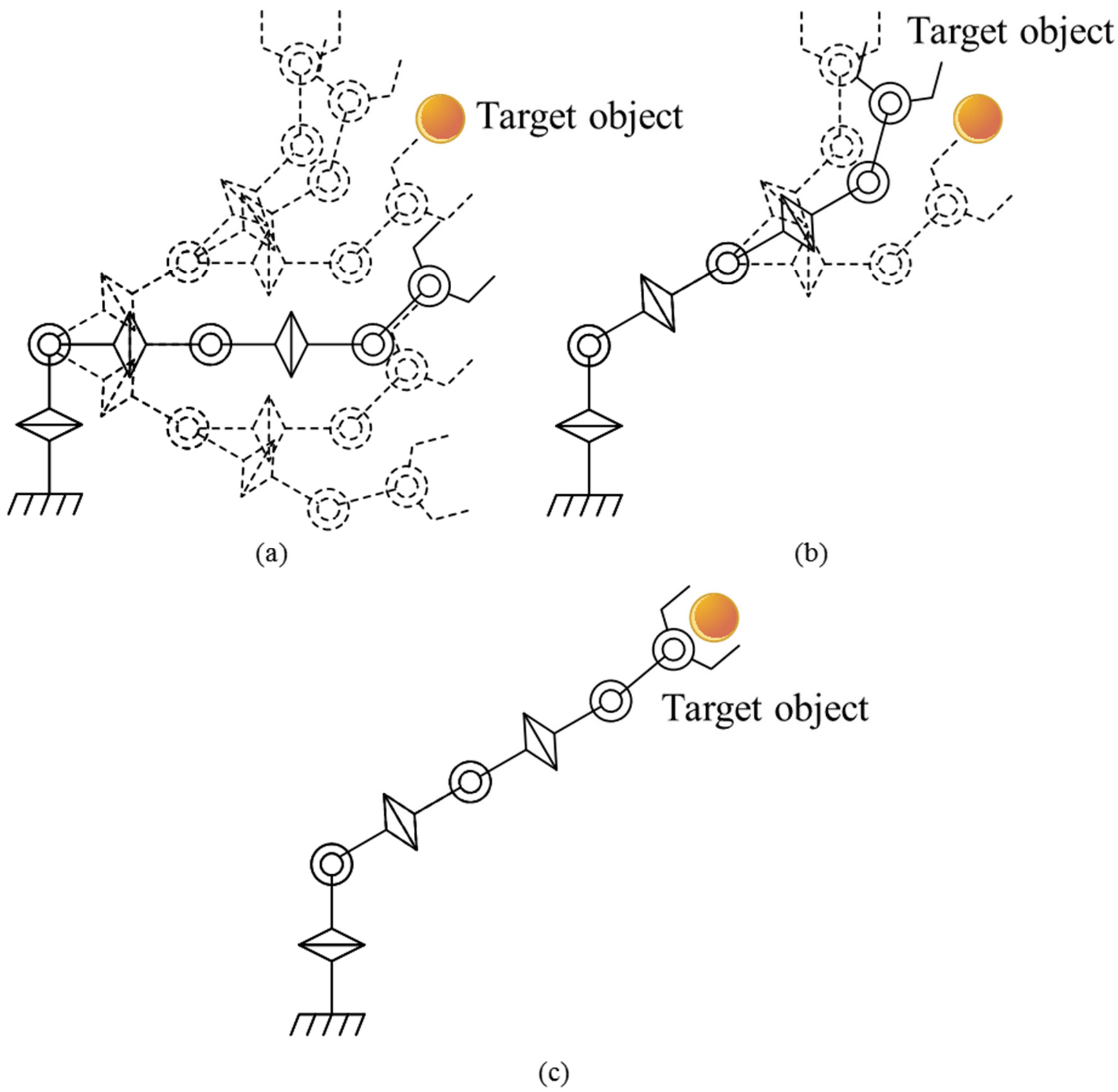


Fig. 2-15 The sequential movement of the robotic arm

Chapter 3

Animal-like Behavior of CONBE Robot using CBA

In our research area of the personal robot, our purpose is to build the robot behavior mimicking an autonomous robot behavior of organisms. Since the robot concept aims attractive to the user that robot consequently is designed relating to the pet as the pet can be easily attractive to human and its behavior can perform an action corresponding to the organism. Therefore, our robot system work is to imitate the action of the pet. To realize the robot interaction relating to organisms, we additionally focus on the principle that base on the creature consciousness and behavior. In this chapter, we describe the briefly background of the cognitive mechanism model of consciousness and behavior of organisms that are used to the imitation of the behavior of creature. Then we consequently explain the CBA system that implement with the robot behavior along with the software architecture, which was developed to realize the autonomous behavior of the robot action in animal behavior.

3.1 Consciousness and Behavior Mechanism of Animal

To design the behavior of animal, that is necessary for the model of consciousness and behavior in order to enhance the action of the robot performing naturally with conciseness based as animal behavior. From a Husserlian phenomenological viewpoint, becoming conscious of an object is a feedback process in which meaning is given to the object. Consciousness directed toward an unidentified object is a process in which the meaning of the object is retrieved from the subject's memory based on observation of it. In the meantime, the meaning of an object becomes more certain as the object identification proceed further. Based on the phenomenological analysis, Tran Duc thao, a Vietnamese philosopher, proposed that the level of consciousness directed toward an object is the one that gives meaning to the object and is the source behavior conducted toward the object, when the behavior is obstructed. This he linked consciousness to behavior development in his conceptual model of the hierarchical relationship between mental process and behavior as who in Table 3-1 (Thao et al., 1986). In this hierarchy, the level of consciousness activated selects and produces an action at the immediately higher level than the level of inhibited behavior. He assumed that the mental process of an animal has evolved in the phylogeny from single-celled animals to humans, just as human consciousness develops in its ontogeny. Comparison studies on the encephalization of animals and ethological studies of behavior development support this assumption.

The consciousness mechanism model of behavior is presented in Table.3-1, when the action is aimed at the target is inhibited for a reason awareness of the action occurs that relates target performs a behavior selection of the top. The first column denotes the level and the second the phylogeny where typical examples are shown. The third column shows the ontogeny where typical ages are shown when the consciousness and behavior of the level first appears, the fourth the consciousness field, and the last column, typical actions the consciousness at the corresponding level triggers. For simplification, animals on the boundaries are ignored, and the infants' ages given in the table are average ones at which the corresponding consciousness and behavior first appears. From this aspect, the consciousness model of behavior includes a nine-level hierarchical structure that correspond to the categories of behavior indicates as shown in Table.3-1. Each level of the action corresponds a consciousness level intensity that has a hierarchical structure from level zero to level eight. The process of consciousness and behavior in table.3-1 describe the process of the consciousness phenomena as the following five features as.

(1) The instant consciousness in each level occur when internal or external action is inhibited on that level.

(2) Consciousness then execute the action in the same level of behavior category which is relating the consciousness directly.

(3) The consciousness related the action does not process when the desire action can perform without conflict from internal or external state.

(4) The action of creature can be appropriately combined the action of below the level of consciousness appearing.

(5) All of consciousness level, which are inhibited, can perform at the same time in consciousness field.

Table 3-1. Relationship between the level of consciousness subject and behavior

Level	Phylogeny	Ontogeny (age)	Consciousness Field	Behavior
8	Man	4 years	Conception	Linguistic actions
7	Man/ape	2 years	knowledge representation	Production of tools
6	Ape	18 months	Symbolic images	Use of tools
5	Monkey	1 year	temporal and spatial relationship by symbols or context	Use of media, geography, mates' motion and ambush
4	Quadruped mammal	9 months	Stable emotion to objects	Detour, search, manipulation of body and limbs, pursuit, evasion
3	Fish	5 months	Temporary emotion to instant circumstance	Capture, approach, attack, posture, escape
2	Earthworm	1 month	Valued sensation of likes and dislikes	Orientation and positioning of body and limbs
1	Sea anemone, jellyfish	0	Primitive perception likes and dislikes	Reflex actions, displacement, feeding
0	any	any	Basic consciousness of awakening	Basic reaction of survival

For more detail, that was described in Table 3-1 on each level following,

(1) Level 0, creature such as Protozoa which is in this level. The action of this level can perform the reaction to instant stimuli from the external stimulation.

(2) Level 1, organism such as anemone, jellyfish or newborn human that belong to this level. For the action of this level, that is related reflex actions, displacement, feeding, corresponding to feeling stimulation of external. For example, the creature move away when it is stimulated by some hatred contact on the other hand it will interested from some perception likes.

(3) Level 2, Human earthworm and 1 month old belongs to this level. In addition, when it exceeds a certain threshold size and duration of the level 1 stimulation, in the sense of sensory area of this level, with the value of the stimulus (love it or hate), the approximate direction and distance is stored. Therefore, consciousness of this level is a coordinate system that is associated value emotionally; disappear at a certain time constant. Until the disappearance, this coordinate system is in the sense that with the direction of the information to be localized movement in the future, be used in the future prediction. That animal is, it becomes possible to predict food, enemy, things and events, such as a fire. However, it is impossible to distinguish between external object from the entire object at this level. Localization move by referring to this sensory area is executed.

(4) Level 3, Human fish and a five-month-old belongs to this level. When the localization movement is suppressed, conscious of this level appears as a ghost. Consciousness of this level, the desire for the front of the eyes of the subject, pleasure, anger, comfort, disgust, is constituted by a moment of emotion, such as fear, the subject is stored as these feelings. Animals at this level has a vision, but can recognize the illusion to a subject by their visual distinction from other things unclear. Feelings of this level is still unstable, at the same time when the front of the eyes of the subject is lost, disappear from consciousness feeling to

the subject. I grasped, escape, approaching, the instantaneous operation of such attacks is performed directly by these feelings. All actions these include the localization movement of the body and limbs belonging to level 2. However, if the subject of the stimulus is strong enough, the animal of this level, it is possible to remember the positional relationship between the emotional value and the subject's body in the sensory area of level 2.

(5) Level 4, Human mammals and nine months old belongs to this level. Grasping Level 3, escape, approaching, the instantaneous operation of such an attack is prevented; it is possible to conduct such this level of bypass and search. In order to allow these actions, there is a need for stable emotion this level. For example, even disappear temporarily prey from view, stable craving a sense of order to have a long-term emotional memory was for the game lasts, it is possible, such as bypass and search.

(6) Level 5, Human lower monkeys and 12 months of age belong to this level. It has a spatial and temporal relationship to a plurality of target, made for grasping the subject to be able to use anything other than the limbs of his body. For example, by such as monkeys or bending shake the branches of a tree; it is a behavior, such as taking the fruit attached to the branches of the first.

(7) Level 6, Human apes and 18-month-old belongs to this level. Use of the tool is, those to be used in other than your own body as in the use of inclusions even if they are not connected to the target product, to use if there is something that can be used in the vicinity of the object. For example, a fruit that is attached to the branches of a tree, is a behavior, such as try with collision with a stick in the vicinity.

(8) Level 7, Person, the human birth 24 months belong to this level. Production tools are in a particular time, under certain circumstances, an action of making the tool as with universal effectiveness that can be used beyond a certain time or circumstances.

(9) Level 8, Person, the human birth 24 months belong to this level. A communication with a mainly symbolic.

Consciousness from level 0 to level 4 is a consciousness to trigger the emotions. Level 8 from Level 5 is a consciousness of the cognitive processes expressed by higher-order brain functions; corresponding action belongs to the category called mainly symbolic action.

For the rest of the system, since we presented the information and the knowledge of the animal consciousness aspect, later with the consciousness perspective that is redesign to the robot cognitive system and implement into

3.2 Recognition Process

The perception system has two fundamental parts as shown in Fig. 3-1. First part is the perception part, which should recognize an external situation using the web camera, and CCD camera, the visual information about the objects is corrected in terms of the shape, size, labeling and the central point of the target-color object. The second part is the calculation of the naturally occurring dopamine waveform and robot's motivation. Subsequently, the details of the recognition process will be described

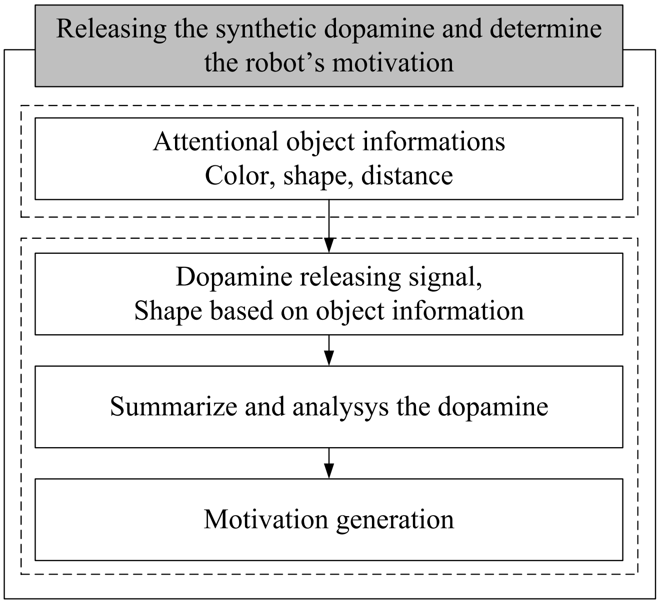


Fig. 3-1 The overview of the perception system in CONBE robot.

For Recognition of the external situation, in this study, CONBE robot uses only the acquired images from the web camera and CCD camera for performing actions and emotional expression, the robot is not usable the other sensors such as the tactile sensor and laser range finder sensor. Thus, it is able to evaluate the rough position of the target object by without the other sensors. The simple image processing techniques for CONBE robot is described as follows.

3.2.1 The Preprocessing of Images

Typically, an important point of the robot control systems is an accurate recognition of the external environment. For example, an autonomous robots that are used in an indoor navigation task based on self-position recognition system and an obstacle recognition system by using the Laser Range Sensor (LRS) and visual methods (Thrun, 2002). However, the most important in this study is to give a consciousness to our robot, is not to emphasize with high-precision formation control. Therefore, the system can simplify the acquired images from cameras by divided into 5 color groups: red, green, blue, flesh-color and the other colors, but only four colors (red, green, blue and flesh-color) that are used to recognize the target objects. And the acquired images are analyzed by using OpenCV (Open Source Computer Vision Library) is an open source computer vision and machine learning software library (Bradski, 2000).

In the simplification of three recognition processes, that are composed of processes following:

- ***Reduce the image size***

The images obtained by the CCD camera (the robot head) and web camera (the robot arm) are read into the personal computer. However, the raw images from two cameras have the high-resolution and are difficult to process in the image processing. So, the original image size should be reduced to a lower resolution as 80x60 pixels, by using cvResize(); function and Bicubic interpolation method in OpenCV library.

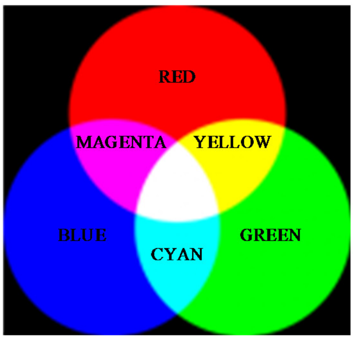


Fig. 3-2 RGB color model

- ***HSV color model***

The RGB color model is based on the theory that all visible colors can be created using the primary additive colors: red, green and blue (in the range of 0 to 255) as shown in Fig. 3-2. These colors are known as primary colors because when combined in equal amounts they produce white. However, if two or three of them are combined in different amounts, other colors are produced. The other model is HSV color model, this model defines a type of color space that is used to generate high quality computer graphic. It is similar to the RGB and CMYK color models. The HSV color space is a composite of three elements composed of hue, saturation and value. Hue is expressed as number from 0 to 360 degrees representing hues red color (0°-60°), yellow (60°-120°), green(120°-180°), cyan(180°-240°), blue(240°-300°) and magenta(300°-360°). Saturation represents the range of grey in the color space. The ranges is from 0% to 100% or sometime the value is calculated from 0 to 1 depending on application range. A faded color is due to a lower saturation level, which means the color contains more grey. Value (or Brightness) works in conjunction with saturation and describes the brightness or intensity of the color from 0% to 100%. When the value is '0' the color space will be totally black color. If the increase in the value, the color space brightness up and shows various colors. The HSV color model is illustrated in Fig. 3-3. Each component (Hue, Saturation and Value) can be determined from the RGB color model by the simple flowchart as shown in Fig. 3-4.

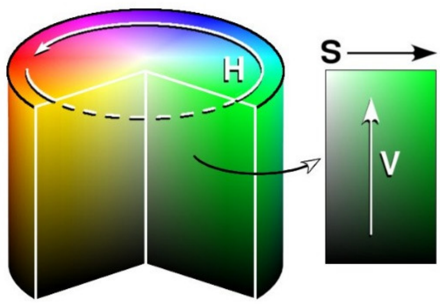


Fig. 3-3 HSV color model

- Specification of images in HSV color model

From the algorithm as shown in Fig. 3-4, the visual information of image (80x60 pixels) can be converted from the RGB color model to HSV color model. The range of each component (Hue, Saturation and Value) used to recognize the target object and human as shown in Fig. 3-5 and the threshold values of each color are defined in Table 3-2.

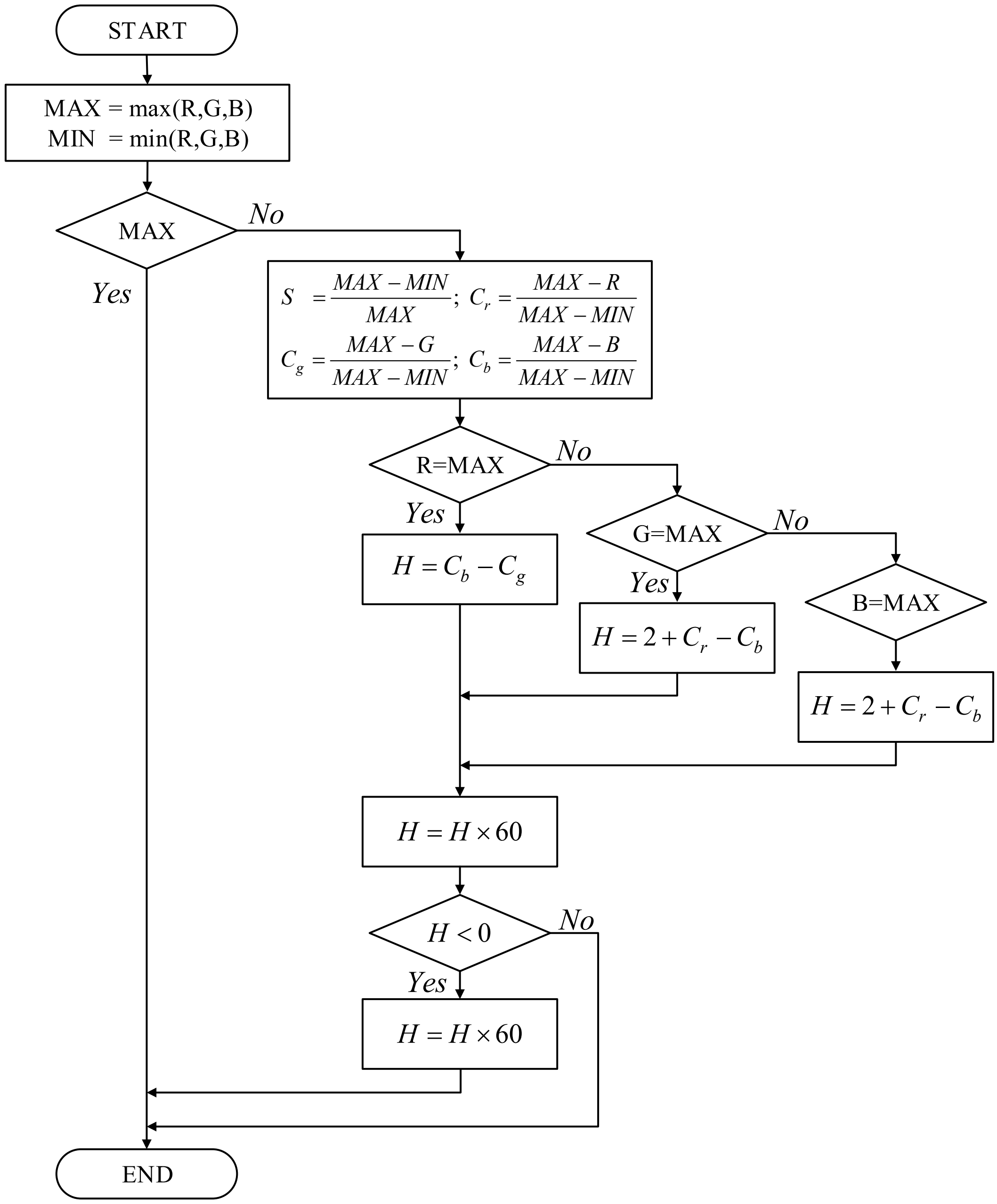


Fig. 3-4 RGB-to-HSV color algorithm

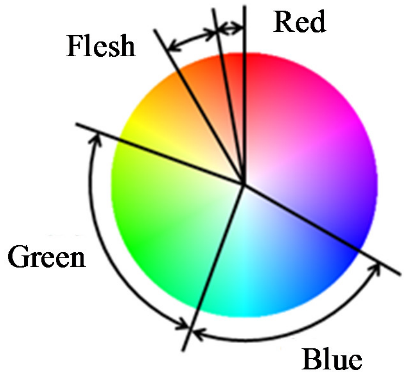


Fig. 3-5 The range of each component in HSV color model

Table 3-2. The threshold values for RGB-to-HSV color method

	Red	Flesh-color	Green	Blue
Hue [°]	0~10	10~30	70~160	160~240
Saturation [%]	59	10	18	39
Value [%]	20	20	20	39

3.2.2 .Labeling Process and Landmark Recognition

- ***Labeling process based on the color of visual information***

Typically, in order to extract specific features of the objects from the image, it is necessary to perform a segmentation process to original image. Therefore, an object labeling algorithm which is used for labeling the distinct objects from a binary (black and white) image is presented. This algorithm is useful for the separation of distinct objects for further analyses applied to each individual object; it is possible to recognize the target object. Fig. 3-6 shows the simplified image and labeling image.

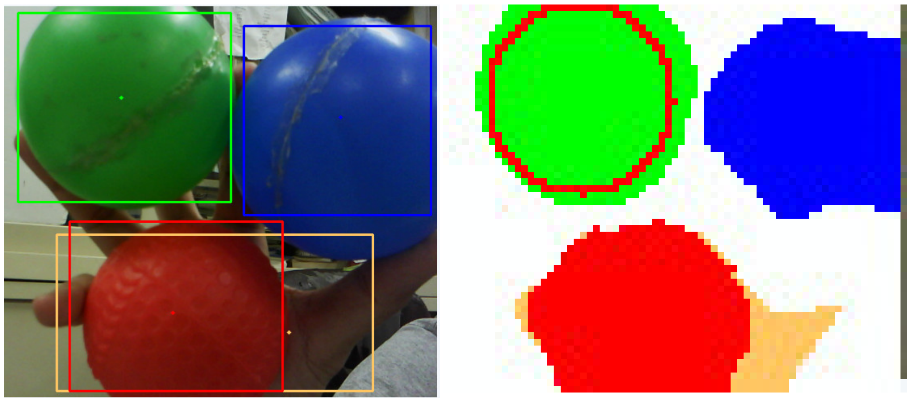


Fig. 3-6 Simplified image and labeling image

- Position recognition of target object

The geometric center coordinates of the obtained color information that will be used to calculate approximately the position of the target object. However, it is very difficult to evaluate the depth perception using the camera. Consequently, in order to recognize the image obtained from the camera, the perspective projection plane is created for determining the position of the target object as described in Fig. 3-7.

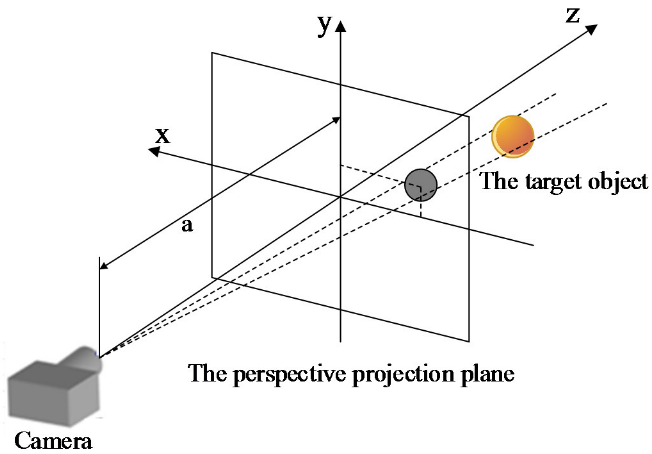


Fig. 3-7 Estimation of a target position

- Shape recognition

However, only the color recognition is not enough to perceive the surrounding environment. Thus, the shape recognition method is considered and used in the recognition process. This method is the drawing circle from the results of the labelling process. Fig. 3-8 shows the example of the details of each element, how to determine the object frame.

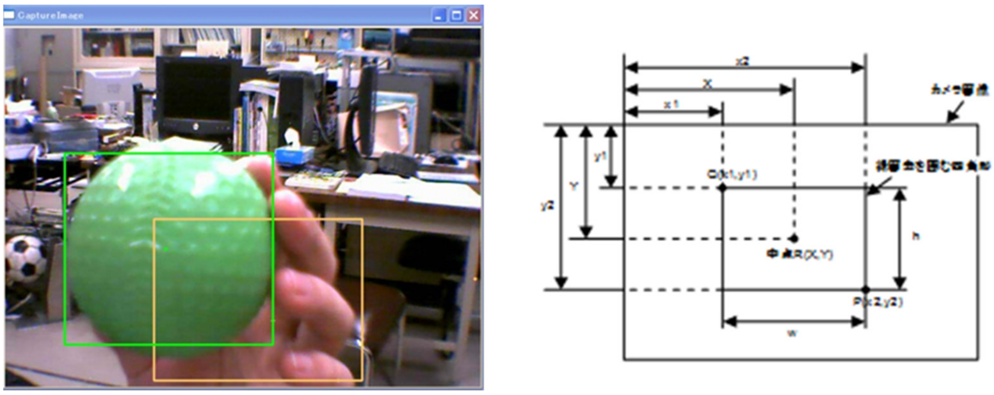


Fig. 3-8 The target object (green ball) frame

First, the results of the original image from labeling process are set the bounding rectangle. $Q(x_1,y_1)$ and $P(x_2,y_2)$ coordinates are used to calculate the size of a rectangle (height and width) and then $O(x,y)$ is determined as the center point. Next step, the radius of the object is calculated in order to draw the circle by comparing the edge of the object frame as shown in Fig. 3-9.

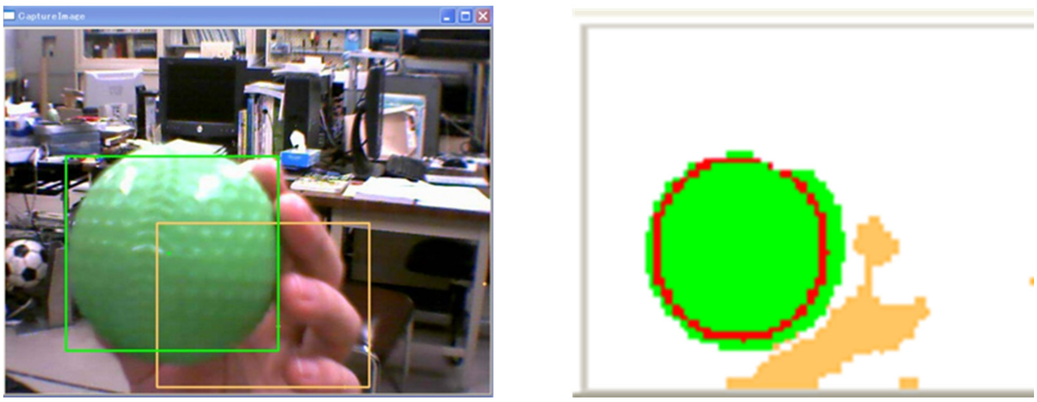


Fig. 3-9 The result of the recognition process

3.2.3 The Desired Settings of the Object for CONBE

When, the CONBE robot performs an autonomous behavior, it should recognize the important components of the object. The images are simplified by dividing into four-color groups: red, green, blue and flesh-color that are distinguished and perception in terms of the shape, size, center-of-gravity position. In this study, the liking behavior is performed when the robot is able to recognize the red or green objects. On the other hand, the robot should perform disliking behavior if it faces of recognizes the blue object. Moreover, the sample color objects are shown in Fig. 3-10.

Fig. 3-10 The sample color objects. (Blue, Green and Red)

3.3 Robot Behavior based on CBA

The robot behavior model has been developed respecting the biological mechanism according consciousness aspect and a brain-inspired learning method for a robot. Here we present the system of the CBA including the synthetic motivation aimed to enable the robot to possess the mentality along with the emotional expression and empathy to share feelings between the robot and a human user. The proposed model may enable humans to feel a closer affinity to the robot compared to what has been achieved with traditional robots. This section covers the robot's perception, the motivation influenced by the neurotransmitter, and then the robot's behavior and its emotion decision based on the CBA.

3.3.1 The CONBE Robot's Structure

Firstly, this section explains the robot structure to describe the relation about the hardware appearance and the CBA system. Here we describe the humanoid-like appearance of the robot's upper body and the concept of the pet robot under the name 'CONBE robot.' The physical hardware of the robot consists of two manipulators and one head.

In chapter 2 that presents the robot dimensional with computer-aided drafting (3D CAD) design and the organization of the hardware that provides the behavior of the robot to make it animal-like. The robot appearance is designed compatible similarly to the semi-humanoid in upper body including the head and arm. In this study, we used CBA based on the phylogenesis. Regarding animal-like cognitive skills, the robot can recognize objects in its environment, e.g., balls and humans. The robot can recognize the color and the shape of a ball for stimulating cognition in the CBA, which consists of the synthetic neurotransmitter and motivation, emotion and behavior modules. The motivation of the robot is stimulated by the neurotransmitter to influence the behavior action.

For an expression with a human, the robot's recognition module consists of the human facial expression recognition (FER) to obtain and perceive a human user's emotional expression. The expression decision will display the robot's eyes expression, in response to the user's emotion and in accord with the robot's EI-based emotion.

Each of the robot's arms is a combination of a six degrees-of-freedom (DOF) arm and three fingers by one degree-of-freedom, which provide a hand-like apparatus. Seven actuators are assembled for the arm construction. Due to the determination of the angle for a multi-joint manipulator, that hardly move to reach the destination position, we then divided the seven DOF into four parts that reflect the human arm, where each element represents a shoulder, an elbow, a wrist and a finger. The entire manipulator length is 450 millimeters. The robots' head along with its vision and expression hardward is 15×15×20 cm. The head includes two-DOF actuators for rotation in the left-right and up-down directions.

For the vision system, we embedded the camera into the head. As part of the system used for the emotional motivation from the environment, the arm is also equipped with a web camera (At chapter 2 in overview of the robot parts, which presented the connection diagram of the CONBE robot system). For the eyes, we used a 2.5-inch display to simulate virtual eyes.

For the design of the CONBE robot, we sought to develop a robot that can create an affinity with the user. The CONBE robot was accordingly designed to have the appearance and behavior of a pet. The next section explain the synthetic consciousness that based on the CONBE robot, which perform its behavior by the arm part.

3.3.2 Hierarchical Artificial Consciousness

In this section, that explains the design and construction of the hierarchical structure of consciousness with the behavior relationship that is formed on the motivation intensity, which we consider, rely on organic psychology. We based this architecture on the psychological process of organisms that evolved in the phylogenesis from a unicellular organism to humans, and on the development of animal consciousness (Thao et al., 1986). The CBA mainly utilizes Tran Duc Thao's synthesis, in which the conscious level ranges from low levels such as that observed in protozoa to the highest level of human. For example, as mentioned above in Table 3-1, level 1 is populated by sea anemone and jellyfish, which can be conscious, such the memory less sensation from the environment. The higher levels are humans and other primates that use symbolic representation. The behavior of an organism is in accord with the activation of the conscious level, depending on the complexity. From this perspective, the link from consciousness to action that is investigated as Tran Duc Thao's model of the hierarchical relationship between cognitive process and behavior.

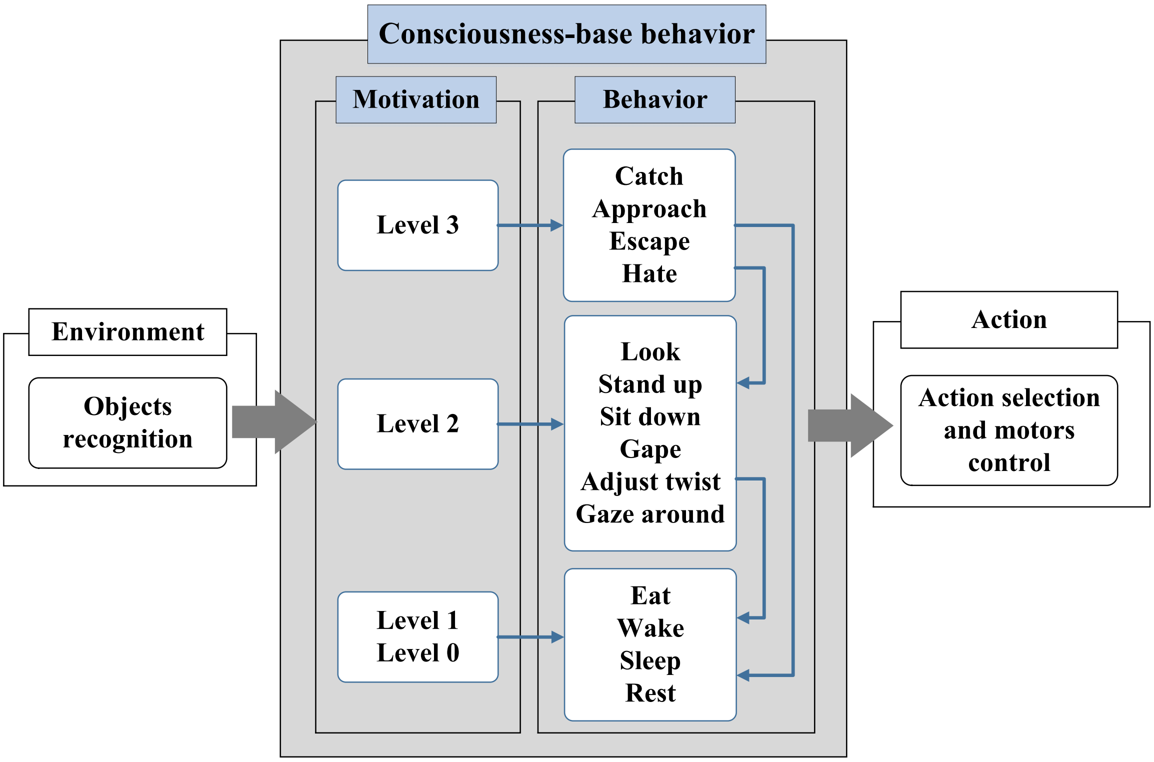


Fig. 3-11 Autonomous behavior motivation based on the CBA, with four levels of motivation (0-3) and 14 behaviors.

In the present study, we divided the consciousness level into four levels in order to construct the synthetic consciousness model that is animal-like such as a fish that consciousness field has the temporary emotion according to instant event or object. As shown in Fig. 3-11, a synthetic four-layer CBA based on Tran's consciousness hypothesis was used. The CBA utilizes the information from the environment and the motivation intensity as criteria for the natural selection of the robot's action. The category of action classified from the low- to high-level module depends on the complexity of the action (McCarthy, 1995).

3.3.3 The Brain-inspired Motivational CBA of the CONBE Robot

In the CONBE robot's cognitive and behavior processes, a motivational model based on the neurotransmitter and perceived information is applied to incite the response in its behavioral process, similar to what occurs in an animal. For example, an animal forages for food in order to survive, and when it finds appropriate food, the motivation then starts activating the animal's desire to eat the food. In addition, an animal begins a hunting strategy that depends on instinct, and it pursues and perhaps catches its prey. The motivation model is the essential factor for the CBA including the synthetic neurotransmitter.

In the mammalian brain, dopamine is the primary monoamine neurotransmitter for reward-motivated behavior, and the motor control and emotional systems are affected by the release of particular hormones by the brain, depending on the stimulus occurring inside or outside of the body. In our research, we thus chose dopamine to be implemented as the significant factor to generate the motivation that is the basis of particular behaviors and emotions depending on the robot perception that can recognize the object using the camera. In the robot's perception, a web camera is employed and embedded in the palm of the hand represents the eyes' ability to visually recognize favorite, hated, and neutral objects. The recognition system can perceive the color, shape, position, and distance of the subject matter as the factors that determine the dopamine level. The system categorizes objects depending on the inclination of the robot, which in our study were set as follows: a red ball was a favorite, a green ball was a minor favorite, other green objects were slight favorites, flesh color was neutral, and any blue object was offensive. An image illustrating how the robot recognizes colors and shapes (as in an animal's perception) is provided in Fig. 3-1.

In our approach to creating an embodied brain system similar to that of animals, we used dopamine for the CBA because dopamine is a major factor in the mammalian brain, affecting emotion and behavior. Additionally, in this system the dopamine could represent a long-term memory, as a robot would experience when an object disappears during the dopamine remaining. The memory could also influence the robot's emotion and behavior in cases of disappearing objects.

The dopamine consisted of the sub-dopamine belonging to each object; e.g., the red-object dopamine produced when a red object appears, the blue-object dopamine, etc. This was done to reflect realistic behavior. We implemented motivation based on dopamine with the goal of enabling a more animal-like action process in the robot's behavior.

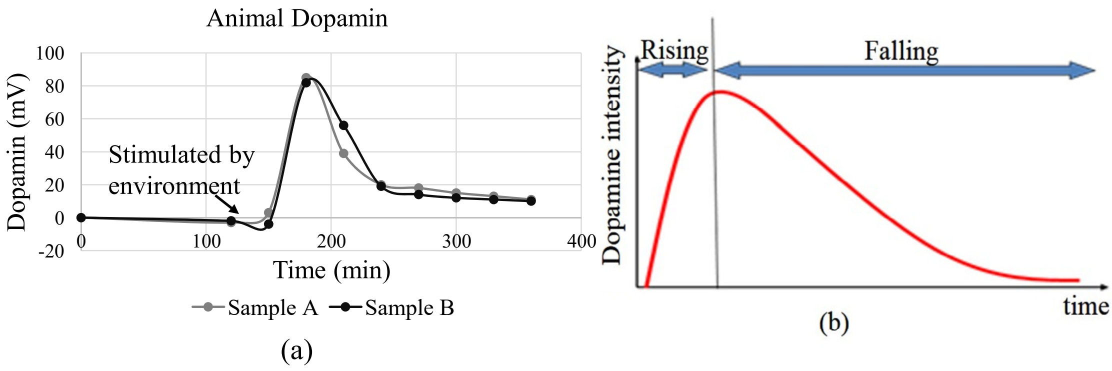


Fig. 3-12 Waveforms of dopamine: (a) a dopamine sample from an actual animal, and (b) the proposed synthetic dopamine.

For the robot's dopamine, we designed synthetic dopamine based on a sample of the dopamine of a rat. A waveform of the dopamine level was portioned out for two sections; i.e., the rising intensity and the falling intensity of the dopamine, as presented in Fig. 3-12.

For the waveform mathematical model, both sections use linear differential equations applied to produce the robot's dopamine. The rising section is given by Eq. (1) below, which is a second-order system, and the falling section is given by Eq. (2), which is a first-order system. In Eq. (1), ξ is the damping parameter, and ω_n is the natural frequency, given input by $u_{(t)}$, given output by $y_{(t)}$, and t is time. For Eq. (2), Tc is the time constant and y_{peak} is the peak value of rising time. Consequently, when many objects appear in the recognition, the system will simplify by summarizing the value of the total dopamine from sub-dopamine of each object to properly induce the motivation.

$$\ddot{y}_{(t)} + 2\xi\omega_n \dot{y}_{(t)} + \omega_n^2 y_{(t)} = \omega_n^2 u_{(t)} \qquad (1)$$

$$y_{(t)} = e^{0.7ex - t\ /\ \mathrm{t\ Tc}\ \ Tc} \cdot y_{peak} \qquad (2)$$

For the creation of motivation, the total dopamine is used to determine the motivation intensity. The waveform pattern of the motivation would emerge with the appearance and acceleration of dopamine inconstancy when the robot's feelings change over time. The system could thus naturally perform animal-like motivation.

The waveform pattern is calculated using a second-order linear differential equation that is comparable to the method of dopamine generation, as illustrated in Eq. (3), where $u_{(t)}$ is the dopamine of each object from Eq. (1) that is used to determine the total of dopamine as $\sum d_o(t)$, and the output motivation is represented by $m_r(t)$. The Runge-Kutta method is then used to continuously determine the synthetic motivation of the robot for forming the motivation pattern naturally, which is calculated by the total dopamine.

$$m_r(t)=2\sum d_o(t)-\frac{d^2 m_r(t)}{\omega_n^2 dt^2}-\frac{2\xi}{\omega_n^2}\frac{dm_r(t)}{dt} \qquad (3)$$

In the robot's autonomous decisions regarding behavior and the determination of the level of consciousness according to the motivation (which is drawn from the previous process of releasing dopamine), this proposed system additionally provides the threshold criterion of the consciousness level depending on the motivation level as an agent. The motivation level from level 1 to level 3 was separated into the negative and positive areas, and level 0 was when the motivation intensity was equal to zero. The range of motivation intensity was between −6.0 and 6.0.

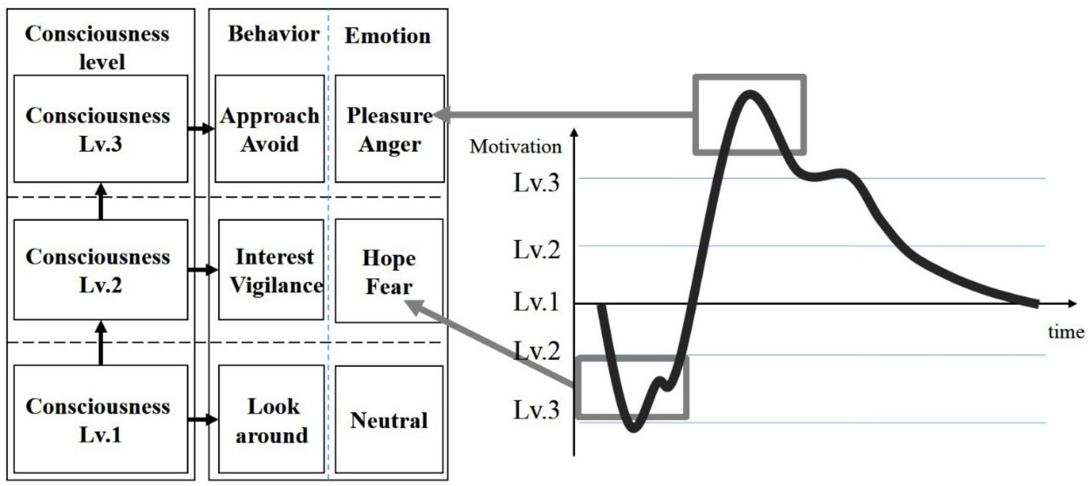


Fig. 3-13 The behavior and emotion selection using the consciousness. The thick black line represents the robot motivation.

Fig. 3-13 illustrates the consciousness criteria of each level at which the robot chooses a behavior and emotion depending on the motivation level and the dopamine information. The behavior and emotion are divided in accord with the consciousness level. For example, the basic actions are at level 1 and actions that are more complex are at the higher levels.

3.3.3.1 Controlling the amount of dopamine waveform

In this section, the stimulus variables are described for controlling the amount of dopamine's waveform such as the natural angular frequency (ω_n), the damping factor (ξ) and the time constant (T_c).

The first stimulus variable is the natural angular frequency (ω_n) that affects the speed of the rising part in the occurrence of dopamine model. The next stimulus variable is the damping factor (ζ), it has effect the peak value of the dopamine's waveform, and the last one is the time constant (T_c) it influences the decay of the falling part of dopamine's waveform. Therefore, in Fig. 3-14, Fig. 3-15 and Fig. 3-16 that show the waveforms of dopamine model when the stimulus variables (ω_n ,ξ and T_c) are changed respectively.

As described above, that is possible to set and generate the naturally occurring dopamine by controlling the stimulus variables according to the external situation.

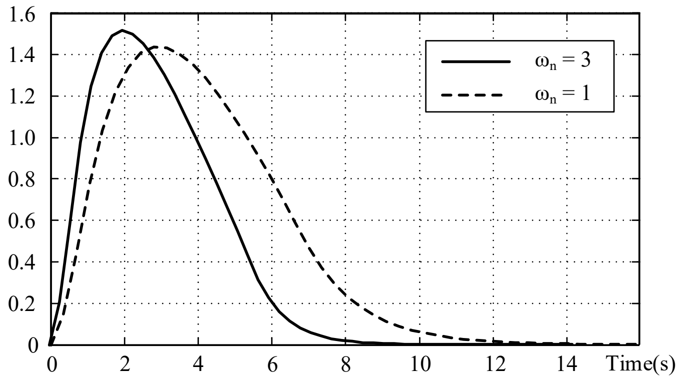


Fig. 3-14 Dopamine's waveform when ω_n is changed

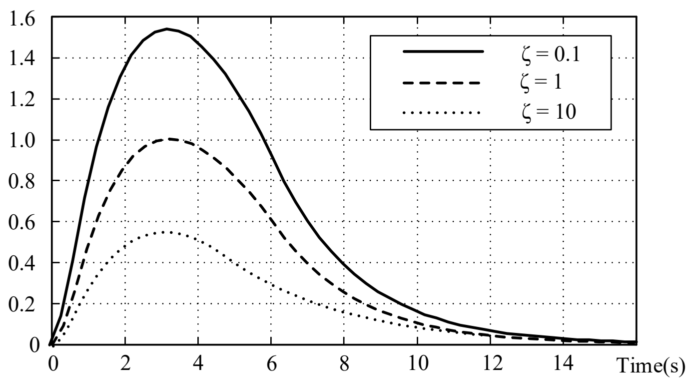


Fig. 3-15 Dopamine's waveform when ζ is changed

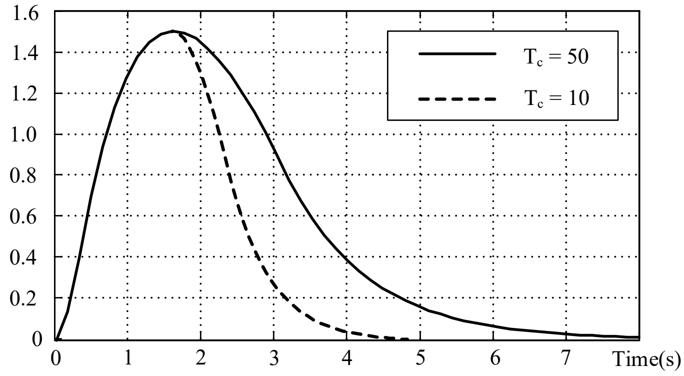


Fig. 3-16 Dopamine's waveform when T_c is changed

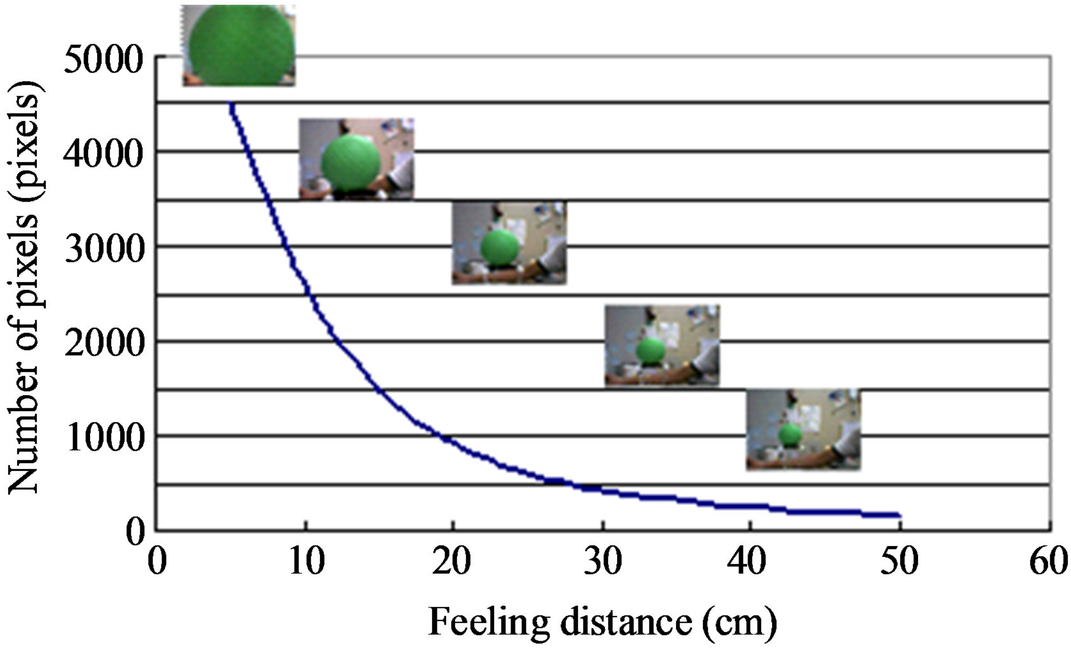


Fig. 3-17 Relationship between the number of pixels and feeling distance

3.3.3.2 Derivation of the feeling distance

The feeling distance (between the target object and the camera) is the important variable that is used for developing the robot's motivation. Therefore, this section will explain how to calculate the feeling distance. Suppose, the green ball (a favorite object) is recognized by a web camera. In addition, the object's distance is changed from 0 cm to 50 cm. The result of the relationship between the number of pixels and the feeling distance is shown in Fig. 3-17.

In Fig. 3-17, the result of waveform seems as the exponential function, thus the relationship between the feeling distance and number of pixels can be expressed by Equations (3-3) and (3-4).

$$Dist = \frac{\log\left(Pixel / 3983.0 \right)}{-0.0682} \; ; if \; 0 < Pixel < 1500 \tag{3-3}$$

$$Dist = \frac{\log\left(Pixel / 7796.0 \right)}{-0.1099} \; ; if \; 1500 < Pixel < 4800 \tag{3-4}$$

The feeling distance will be used as the input variable for calculating naturally occurring dopamine and determining the stimulus variables.

3.3.3.3 Determination of the stimulus variables

In this section, the stimulus variables are specified by the conditions of the liking object (green object) and disliking object (blue object) recognitions.

- Condition of the liking object (green object)

Here, the setting parameters are assigned in the conditions of the favorite object when the robot is able to recognize the liking object. In this situation can divide into 4 conditions for generating the dopamine's waveform as:

- When the robot can recognize the green object at the first time.

The movable range of the robot arm and the feeling distance are used to set the stimulus variables as expressed by Equations (3-5), (3-6) and (3-7), where *Feeling dist* is the feeling distance of the robot and $Movement\ dist$ is the movable range of the robot arm.

$$\omega_n = 10.0 \tag{3-5}$$

$$\zeta = 0.1 + (Feeling\ dist/10) - (5Movement\ dist) \tag{3-6}$$

$$T_c = 60.0 + 60.0\{(50 - Feeling\ dist)/100 + Movement\ dist\} \tag{3-7}$$

- When the distance between the green object and the robot's hand has changed.

In this case, when the distance is changed between previous time and current time, which interprets as the shrinking of the dopamine's waveform or the expanded waveform. $diff\ vallue$ is the variable that presents the different value of the feeling distance as expressed by Equation (3-8), where $Feeling\ dist\ back$ is the feeling distance at the previous time and $Feeling\ dist$ is the feeling distance at the current time.

$$diff\ value = e^{\left\{(Feeling\ dist\ back - Feeling\ dist)/50.0\right\}} \tag{3-8}$$

Therefore, in this case, the setting parameters are calculated by Equations (3-9), (3-10) and (3-11).

$$\omega_n = 10.0 \tag{3-9}$$

$$\zeta = 30.0/diff\ value \tag{3-10}$$

$$T_c = diff\ value \tag{3-11}$$

- When the green object is unmoved.

The stationary state is defined by the center of gravity point is not changed. In this state, the stimulus variables will be assigned as $\omega_n = 20.0, \zeta = 15.0$ and $T_c = 0.05$. Nevertheless, if the green object is not the same position, T_c will be increased in order to decrease the dopamine level dramatically correspond to the Equation (3-11).

➢ When the green object is a ball

In this situation, that is similarly the previous condition (if the green object is unmoved), it means the robot can recognize the green ball for a long time, the dopamine is continuously increasing. And the setting parameters is also $\omega_n = 20.0, \zeta = 15.0$ and $T_c = 0.05$.

- Condition of the disliking object (blue object)

The other condition is described when the robot recognizes the blue object (disliking object). In this case, it can divide as 2 conditions for generating the dopamine's waveform:

➢ When the robot can recognize the blue object.

In this study, the robot should perform disliking behavior or negative emotion when it can recognize the blue object. In addition, for this situation the robot does not need to consider the movable range of the robot. The dopamine's waveform is represented as the negative value and the all-setting parameters are also indicated by Equations (3-9), (3-10) and (3-11).

➢ When the feeling distance of green object and blue object are different

In this case, that describes about the recognition of the green and blue objects at the same time. Equations (3-8) and (3-9) are used again for calculating the feeling distance of blue object ($Dist\,Blue$), in order to determine the ratio of the feeling distance between the green object and blue object ($Ratio\,of\,GtoB$) as illustrated in Equation (3-12).

$$Ratio\,of\,GtoB \;=\; \frac{Dist\,Green}{Dist\,Blue} \tag{3-12}$$

If $Ratio\,of\,GtoB \geq 1$ that means the blue object is near the camera, the negative dopamine is increasingly created. The setting parameters are set by $\omega_n = 20.0, \zeta = 15.0$ and $T_c = 0.05$. On the other hand ($Ratio\,of\,GtoB < 1$), the time constant will be modified by multiplying with the ratio of the feeling distance as expressed in Equation (3-15).

$$T_c \;=\; T_c \cdot Ratio\,of\,GtoB \tag{3-13}$$

3.3.4 Calculation the Intrinsic Robot's Motivation

From the computation of the naturally occurring dopamine model as described above, the total sum of their positive (the green object) and negative (the blue object) values that is used as the input variable for calculating the robot's motivation shown in Fig. 3-18 and the motivation waveform is estimated by the 2nd order system of linear differential equation as expressed by Equation (3-14).

$$\begin{aligned} Robot's\,motivation(t) \;=\; & 2 \cdot Total\,of\,dopamine(t) \\ & -\frac{1}{\omega_n^{\;2}}\frac{d^2}{dt^2}Robot's\,motivation(t) \\ & -2\frac{\zeta}{\omega_n^{\;2}}\frac{d}{dt}Robot's\,motivation(t) \end{aligned} \tag{3-14}$$

Here, $Total\,of\,dopamine(t)$ is the total of the naturally occurring dopamine that is described in the above section, $Robot's\,motivation(t)$ is the output variable, ω_n and ζ are considered by the outside environment and the internal state.

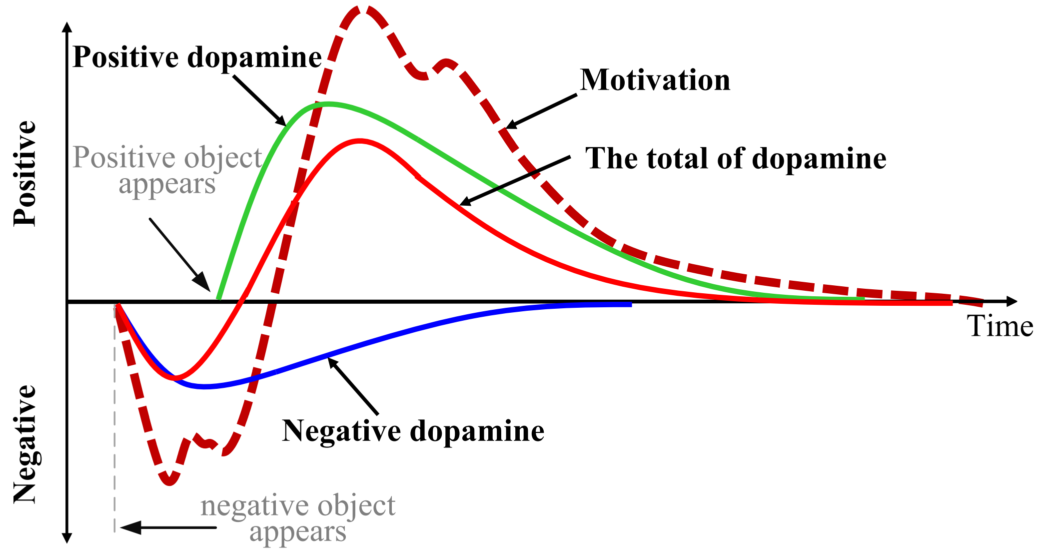


Fig. 3-18 Robot's motivation model

3.4 Summary

The consciousness theory relating to psychology perspective was described in this chapter since that is the needed knowledge to design the synthetic consciousness architecture. The consciousness' aspect has been described and synthesized to be a consciousness-based architecture (CBA) in this chapter. With our purpose, the realization of autonomous behavior of the robot could mimic the realistic behavior of an organism. Later, the overview of the proposed system is thoroughly described that consist of three major processes: the recognition process, cognitive process and behavioral-emotional expression process. The proposed system is executed by the CONBE robot in a realistic environment.

Chapter 4

Emotion Generating System of CONBE Robot

The robot system and behavior system based on the CBA were presented in the previous chapter that is a basis method of the research proposed. The system is to imitate the animal behavior based on the dopamine and motivation criteria for selecting an action with predefined. This chapter presents the overview proposed framework, methodology, and implementations. Firstly according to the objective, the CONBE robot with cognition and consciousness based on the animal behavior model resembling that of human beings or animals is increasing the impact to a useful facility of an intelligent autonomous machine that can achieve a more effective relating for robot behavior. In this thesis, the proposed method has been focused on considering and developing the emotional generation system performing based on the primary structure of a hierarchical synthetic model of consciousness to its behavior. The process of the cognitive system relies on the animal that produces an action from the sequence of processes as Recognition and Perception, Motivation, Behavior selection and Emotional expression by using the brain-inspire method.

The intelligent emotion and behavior generation and expression system, containing with subsystems are presented in the chapter that autonomously determines and outputs the most proper behavior and emotional expression based on internal and external state variants. From the primary structure as described above, the behavioral-emotional selection system can be divided into three processes. We have been developing the personal robot that can represent its behavior aroused by the motivation and synthetic neurotransmitter performed by dopamine. The neurotransmitter is modeled for stimulating motivation and self-behavior embodiment of robot to the robot approaching the creature naturalness along with expressing its natural posture or decision. Therefore, we designed the consciousness and behavior robot named by "Conbe robot". Two arms and one face with respect to semi-humanoid architecture constructed this robot (Chumkamon et al., 2015). In this thesis, we propose the framework of the robot based on animal behavior and emotion model that is to allow the animal robot to be able interacting with human properly. This main system proposes the cross emotion expression from the robot toward human and cross facial emotional expression perception. Additionally, the robot's expression would interact with the user using the consideration by robot's emotion and user's expression. The emotional expression uses the face of the robot emotion or in the case of a manner in human facial expressing the robot would appropriately express the facial emotion according to the sharing emotion between robot and its inside state of cognitive and emotion. The user then get interested in the robot because the robot can care about the user emotion.

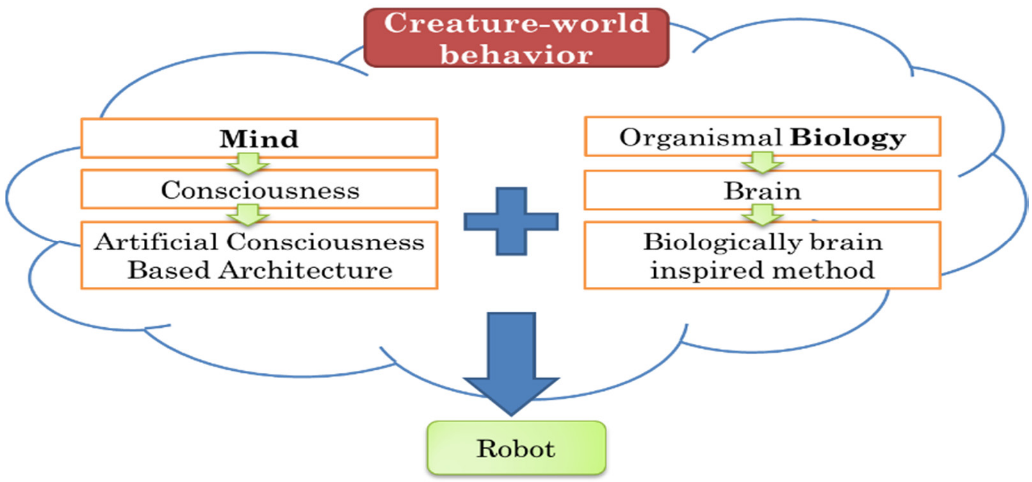


Fig. 4-1 The proposed initiated concept from the aspect of the combination between mind and organismal biology.

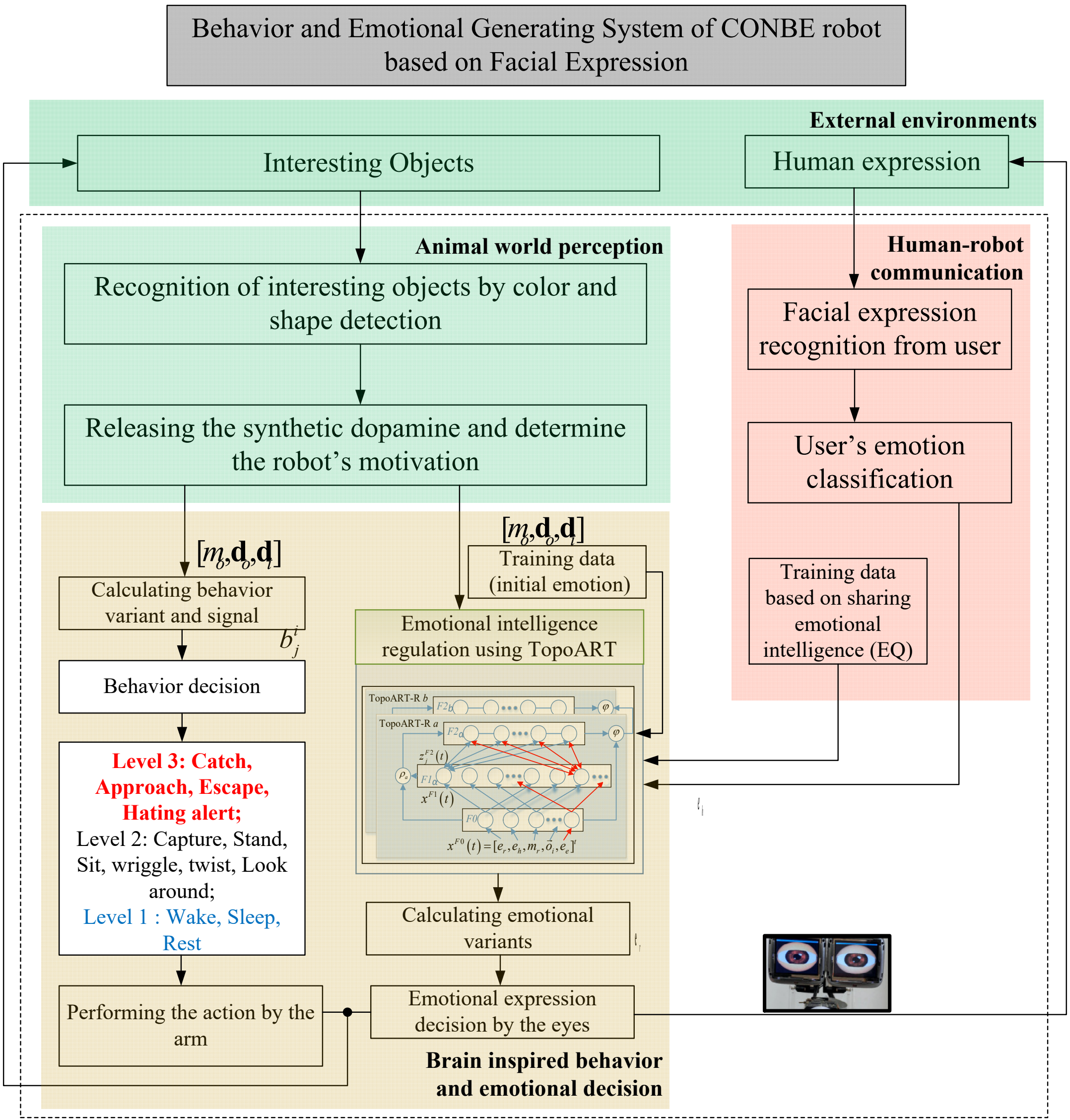


Fig. 4-2 The overview of the proposed methodology. (In this framework, The main part consist of two section including animal perception-behavior and human communication performing for emotional intelligence system)

4.1 Proposed framework

Regarding the concept of emotional intelligence (EI), our proposed robot is also designed to consider the social etiquette that humans use for emotional expressions. To illustrate, if you are happy while your friends around you are feeling sad, when you recognize your friends' sadness you might deliberately express an emotion other happiness because relationship conflict might develop if you express an emotion opposite that of your friend. You might show neutrality or pretend to be sad in order to share your friends' feeling and express sympathy in order to maintain the relationship. In effect, you alter your facial expression and demeanor to maintain human relationships. A robot should thus have similar ‘empathy’ and ‘sympathy’ (as illustrated in Fig. 4-1 and this topic is the primary focus of this thesis.

Here we focus on points that were not applied in recent studies of personal robots or HRI based on a framework of animal behavior/biologically inspired robots. We designed the proposed system shown in Fig. 4-2.

With this system, the robot interacts extensively with its environment, including using perception as a higher-order animal would, plus consciousness-based architecture (CBA) and human interaction. The robot additionally performs the cross-communication of expression as it uses its EI skills to be an instinctive companion or pet for humans. The following are the major points of our proposed system.

- Pet robot design with a head and face for expression cross-communication between human and animal robot
- An animal-behavior robot based on the CONBE robot, using CBA including the motivation system
- Empathy skill enabled by facial expression recognition, and emotional expression based on emotional intelligence
- Emotional expression decisions based on the biologically inspired network of TopoART

We implemented the above functions in the CONBE robot and performed the experiment described in the following section. The framework was built to provide the robot with natural behavior, so that it can communicate with humans, and enabling the robot to express emotion including its internal feeling state and EI-based expression in each circumstance. Thus, toward the goal of providing a friend for humans, we designed a robot with the above-mentioned functions.

Humans and other animals such a mammal which has a sophisticated biological brain, are an integration of mind and physical biology (Robinson, 2011; Young, 1990). In light of this integration, we designed a robot framework that includes the two fundamental roles of mind and biology in which the robot's consciousness function stands for the major role of mind and its 'brain' functions as the biology. We applied the hierarchical architecture of consciousness based on the phylogenetic evolution of living organisms to a system for the cognitive processes in animal-like behavioral and emotional regulation systems of the robot. We also applied the TopoART representing the artificial brain and consciousness perspective to the system for the emotional intelligence model of the robot's expression. For the beginning part of the action of the robot in its behavior that is the perception system which is to obtain the contact of sense. In this robot, the perception is mainly depending on the vision system that the robot can recognize the object by the color and shape.

The robot expression is mainly determining rely on the instance emotion of robot, which is arousal by the motivation, and rely on the human emotional expression. Because we would like to make a robot not only express its emotion such a conventional work but also the robot expression should engage with the user expression with sharing the owner robot. Therefore, we investigate the part of emotional intelligence study for robot expression correspondingly without conflict. The sharing emotion is the one part of the EI that concerns components of human behavior, which provides for coexisting with others to maintain the relationship each other. Therefore, the robot should similarly provide sharing emotion to live with human users without conflict. For the EI of robots that contain subsystems that are designed to include the recognition of human emotions, the EI regulation could use TopoART-R and the expressions provided by the robot's eyes.

4.2 User facial expressions recognition

In emotional expression with humans, a robot must know and recognize the emotions that the robot should express. We therefore attempted to develop a robot that can emotionally express with humans in the various environments formed on the CBA. The system that we created provides human facial expression recognition, using facial detection and an algorithm for localizing facial features. For the implementation of these methods, we used the OpenCV library (opencv.org) to code the software.

First, the vision system would obtain an instant image from the camera embedded in the robot's face. An algorithm then performs the face detection; we used the algorithm of the Haar-based cascade classifier for face detection that can sufficiently detect a face quickly and accurately (Viola and Jones, 2001, p. 200). The face detection also functions to identify the orientation of the face and to preprocess the data for the facial feature extraction that is operated by the constrained local model (CLM).

4.2.1 **Facial feature extraction using the CLM**

The CLM is an ingenious method that can be used to illustrate and indicate deformable objects or facial images, and many studies have applied it (Lucey et al., 2010). The advantage of the CLM stems from its use of the correlations among several small patches and an originated shape model, as well as its robust and rapid tracking of unseen images. The active appearance model (AAM), which is a precise model for localizing the feature such as facial features, has also been used frequently in robotics (Edwards et al., 1998).

Compared to other related methods, the CLM is more efficient for person-independent face alignment because the CLM uses small local-region templates to achieve local matches in testing images. The CLM is necessary to provide images for training the models and defining shapes, which consist of the landmark points and the connections between the landmark points, which is shown in a 2D lattice. For example, the shape s of n landmark points is determined by Eq. (4-15).

$$s=[x_1,y_1,x_2,y_2,\ldots,x_n,y_n]^T \tag{4-15}$$

With the relation of the shape model and path model which store the small local texture from each vertex that is also used in shape model, the small area of each vertex which corresponds around to a texture of face image. In Eq. (4-15) we use x_n to represent$[x_n,y_n]$, and then the equation would be reformed by $s=[x_1,\ldots,x_n]$ where $x_i=[x_i,y_i]$ in 2D coordinates for the image view. There, T samples are from the data training extraction from the images that we selected to train, and we specified the landmark points in the small region.

We also estimated the scale, rotation and translation by all samples, and then performed a principal component analysis (PCA) for the approximated means. For the proposed work, we implemented the model as a non-rigid shape variation. A point distribution model (PDM) would be composed with the generalized rigid transformation, locating the shape vertices with the given image.

$$x_i(p)=s\mathrm{P}\mathbf{R}(\bar{x}_1+\mathbf{\Phi}_i\mathbf{q})+\mathbf{t};(i=1,...,n) \quad (4\text{-}16)$$

where P={s,α,β,q,t} represents the model parameters, which are the normalized scaling s, the rotation angles in 2D coordinates α and β, a translation of the shifting point **t** and the non-rigid transformation parameter **q**. $\bar{x}_i$ represents the mean position of the i^{th} landmark, and **P** denotes the projection matrix. We assume that the prior parameter can be normalized into a zero mean in a distribution and variance Λ at parameter vector **q**, where x_i points in the PCA provide $\bar{x}$ in Eq. (4-16) and Λ in Eq. (4-17).

$$p(\mathbf{p})\propto N(\mathbf{q};0,\Lambda) \quad (4\text{-}17)$$

The PCA of the point distribution model (PDM) is applied to construct in the CLM and works with local or patch experts. For patch models, we used a classical probability method of 2D-Gaussian distribution to estimate the landmark error points. We then constructed the CLM model by constructing a shape model and a trained patch model whose yields are considered independent and are multiplied.

$$J(p)=p(p)\prod_{i=1}^{n}p(l_i=1|x_i(p),I) \quad (4\text{-}18)$$

Eq. (4-18), where l_i denotes a random variable indicating whether the i^{th} landmark falls within its regional area, $p(l_i=1|x_i(p),I)$ is the probability of I image, and x_i indicates whether the i^{th} landmark is in its area. Additionally, another attractive detail of the CLM algorithm that was previously explained, which also presented the novel algorithm and compared the experiment with AAM by using human face images and magnetic resonance brain images (Cristinacce and Cootes, 2008). We built the facial models using the CLM. Fig. 4-3 presents the shape and patch models of the type used in the present study (Overview of FER). To prepare the process of expression recognition, we extracted all connectivity to be the length vectors, which are used to predict the expression recognition when the CLM shape model tracks the facial features during the performance of the CLM.

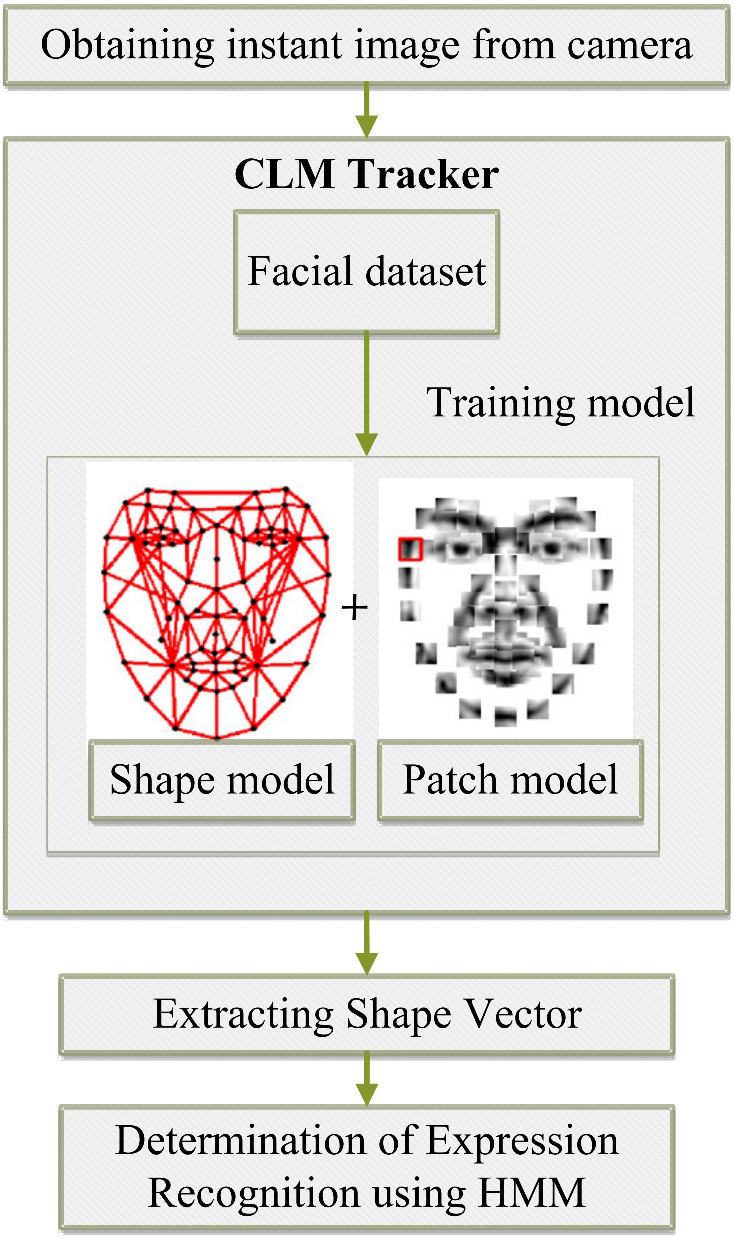


Fig. 4-3 The overview of the facial expression recognition (FER) system.

For the model construction and testing of the CLM, we used a camera embedded in the robot's face, which provides instant images of the human user. The system first performs face detection to locate the user's face dimensions, and it then performs facial feature extraction using the CLM. For testing the feature extraction using the CLM, we trains the model using sample facial images for construction of model. We then used 10 facial images with a practice environment as a background to train the CLM. The shape model is defined by 80 landmark points and 187 connections, because these parameters are sufficient for constructing the model to perform. The CLM was trained to construct a shape model and a patch model for features fitting the test images. Fig. 4-1 shows sample capture images for the facial features tracking, including a special case with a face wearing glasses.

The extraction of a facial dataset represented as a graph is provided by Fig. 4-2, which was concatenated by the link length of all connectivity of the facial shape model tracking from an instant image, in which the x-axis indicates the sequential number of each connection and the y-axis indicates the length of the link.

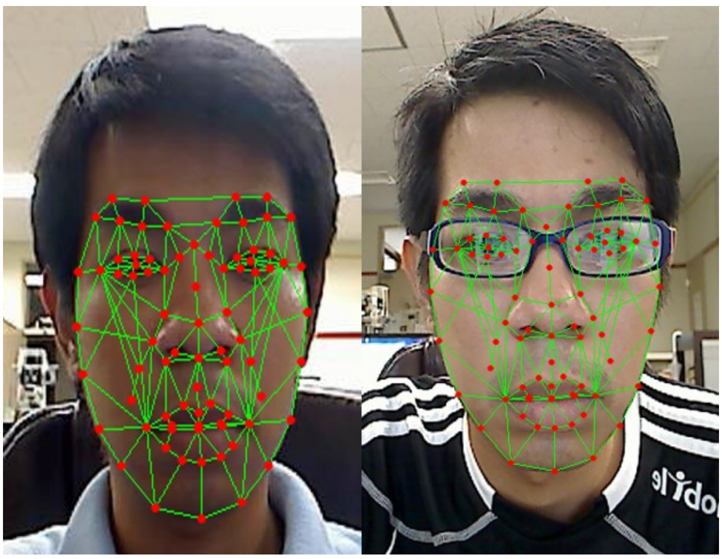


Fig. 4-1 Examples of capture images used by the robot for tracking facial features.

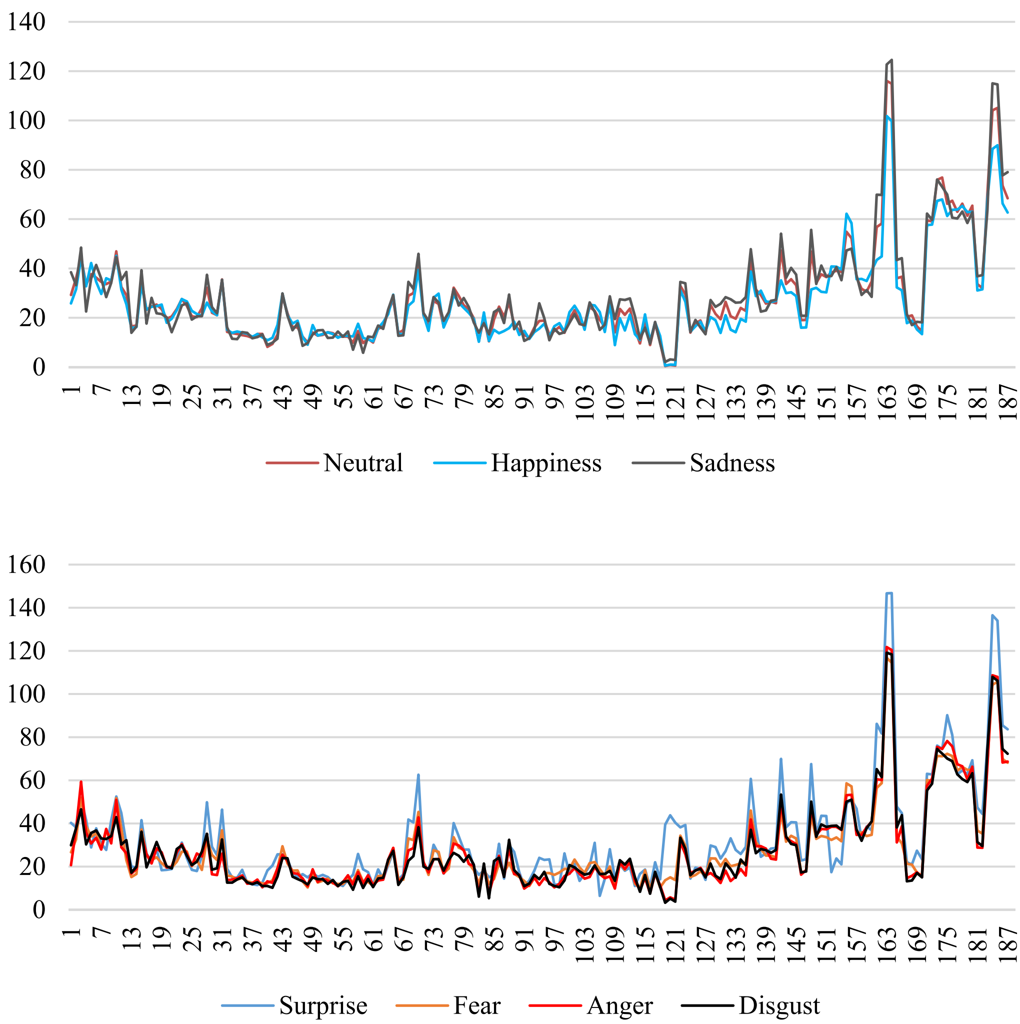


Fig. 4-2 Instances of facial feature extraction by the robot.

The facial parameters would be the main data to be analyzed for the classification of emotions. The results of the execution time in the additional test are shown in Fig. 4-3. In this experiment, the CLM had an average execution time of 27.97 milliseconds; this means that the frame rate would be approx. 35.75 frames per second. As we can see by the results, more complexity is required to distinguish the facial parameters for determining what the emotion is expressing.

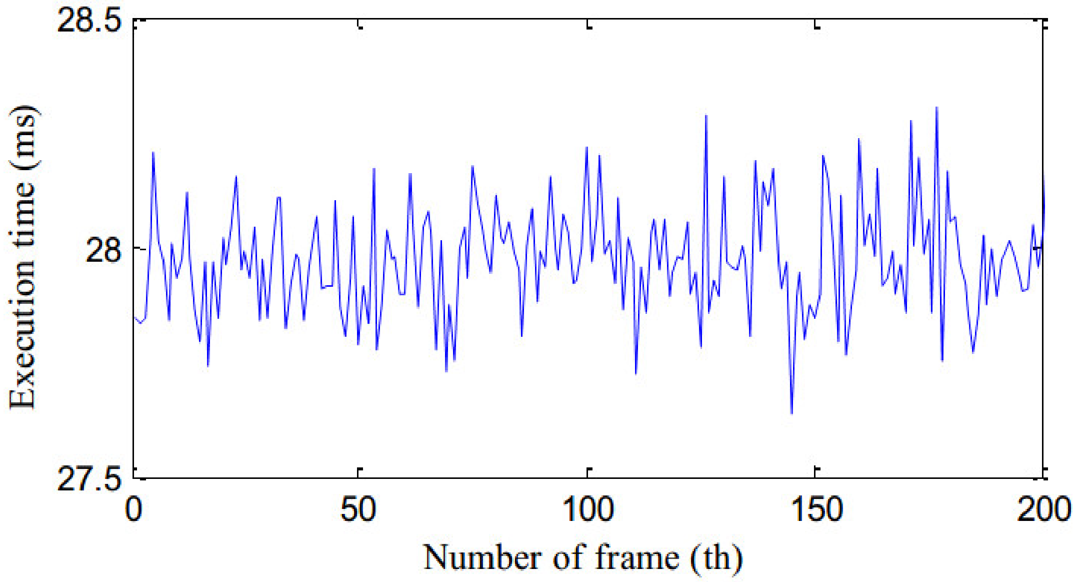


Fig. 4-3 The CLM execution time.

4.2.2 **Recognition of emotions based on facial expression**

After the CLM algorithm provided the facial parameters, we used an HMM to achieve the emotion classification using the results of the facial feature location analysis. The facial feature locations are extracted by the CLM and loaded to the HMM to determine the facial expression. As the algorithm for training the model, we used the single Gaussian probability model. The object of an HMM is the evaluation, decoding, and training determined by the Forward, Viterbi, and Baum-Welch (BW) algorithms, respectively. We used the BW re-estimate method to model the facial expression into the HMM, in which we used a left-right model. For the HMM, $\lambda^{(k)}=\left(A^{(k)},B^{(k)},\pi^{(k)}\right)$, which is the notation of the HMM procedure that we used for constructing the expression models (Rabiner, 1989). S_i to S_j are the state transition probability that represented to $A^{(k)}=\{a_{ij}^{(k)}\}$. The observation probability o at state S_j is represented by

$B^{(k)}=\{b_j^{(k)}(o)\}$ and the initial state probability distributions are represented by $\pi^{(k)}=\{\pi_j^{(k)}\}$.

For a continuous-density HMM, we used a single component Gaussian distribution as the observation probability distribution given by Eq. (4-19):

$$b_j(o)=\frac{1}{\sqrt{(2\pi)^n \left|\sum_j\right|}}\exp\left(-\frac{1}{2}(o-\mu_j)^t \sum_j^{-1}(o-\mu_j)\right) \tag{4-19}$$

where μ is a mean vector and $\sum_j$ is a covariance matrix, we solved the problem by Viterbi training or the Baum-Welch metho. As the objective in our recent study, we used a BW algorithm. For the objective of the recent study, we used a Baum-Welch algorithm. For the classification of facial expressions, the HMM trained the model for eight facial expressions (i.e., surprise, pleasure, hope, neutral, fear, sadness, disgust and anger). The concept is that the given face is similar to a certain class, and that particular class is the solution. Fig. 4-3 also provides the overview of the FER system including CLM facial extraction, where the system can recognize emotions such as surprise, happiness, neutrality, fear, sadness, disgust, and anger.

In our classification of emotions experiment using the HMM, we divided the set of 434 facial images without glasses into 84 training images and 350 images for testing, which means there were 12 training images per emotion and 50 testing images per emotion. Seven emotions were used: neutrality, happiness, sadness, surprise, fear, anger and disgust. For the training HMM, we constructed three types of HMM: 80-state, 100-state, and 120-state models. After we set up the system, we tested the testing images, which are the unseen dataset. The results of the 80-state, 100-state, and 120-state models are given in a confusion matrix of the percentage recognition in In our classification of emotions experiment using the HMM, we divided the set of 434 facial images without glasses into 84 training images and 350 images for testing, which means there were 12 training images per emotion and 50 testing images per emotion. Seven emotions were used: neutrality, happiness, sadness, surprise, fear, anger and disgust. For training the HMM, we constructed three types of HMM: 80-state, 100-state, and 120-state models. After we set up the system, we tested the testing images, which are the unseen dataset. The results of the 80-state, 100-state, and 120-state models are given in a confusion matrix of the percentage recognition in Fig. 4-4, Fig. 4-5 and Fig. 4-6, respectively.

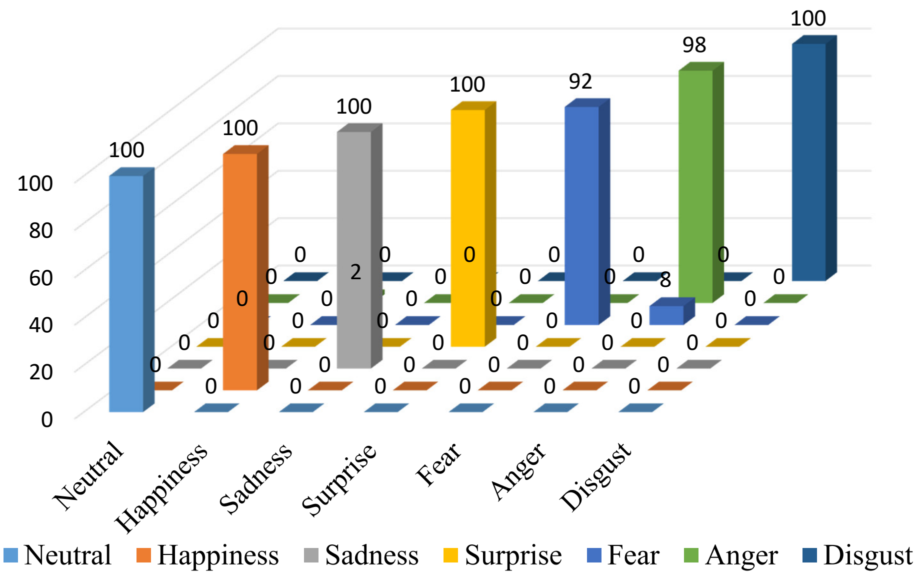


Fig. 4-4 The confusion matrix of the 80-state model.

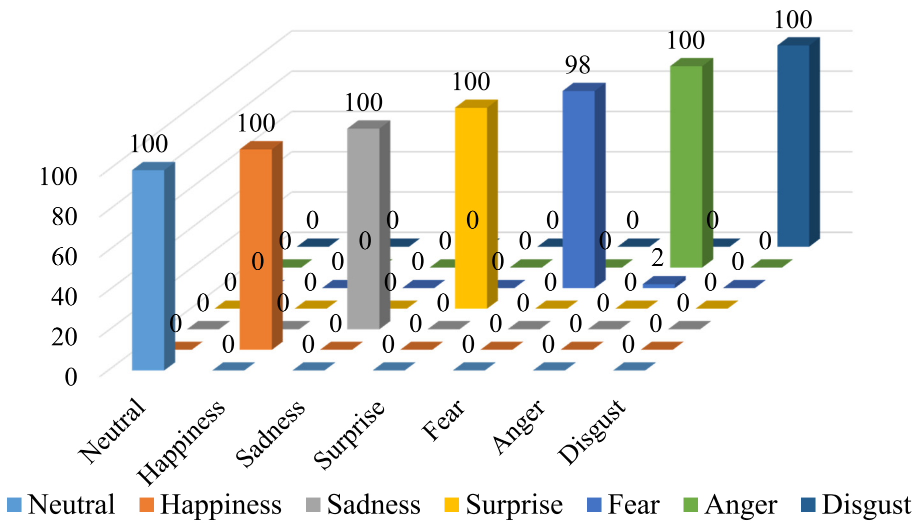


Fig. 4-5 The confusion matrix of the 100-state model.

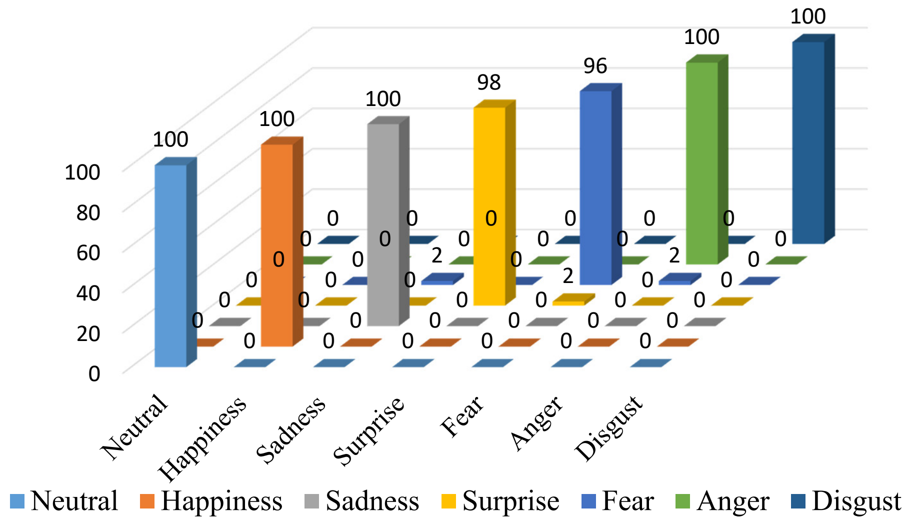


Fig. 4-6 The confusion matrix of the 120-state model.

The results showed that the 100-state and 120-state models were better than the 80-state model. However, all three models gave excellent results for the classification of emotions. The correct percentages of the emotion recognition for the 80-, 100-, and 120-state models were 98.6%, 99.7% and 99.14%, respectively. We used the 100-state model because the 120-state model took a long time for the calculation.

Neutral

Pleasure

Sadness

Surprise

Fear

Anger

Disgust

Fig. 4-7 Capture images of a human user's facial expressions from the CONBE robot's dynamic recognition of emotion system.

The results of the dynamic recognition system eventually showed that the images were captured while the system was processing in real time (Fig. 4-7). We also experimented with the facial expressions by a face wearing glasses, and we found that the recognition system could still recognize those facial expressions as well.

4.3 Adaptive Resonance Theory

Adaptive Resonance Theory (ART) method is a brain-inspired method that use to address self-organization and stability of recognition regulations for unconstrained sequences of the input pattern (Grossberg, 1976). From the beginning of ART background, the architectures were initiated for analyzation of the instability inherent feedforward adaptive coding model. Due to the realistic data, the information encounters the condition where is the data is changing continuously and unstable. In that case, all the system confronts learning the plasticity-stability dilemma. For this dilemma dealing, a system that must be able to learn to adapt to a changing environment (i.e., it must be plastic) but the constant change can make the system unstable, because the system may learn new information only by forgetting everything it has so far learned. Since ART presented an approach regarding to the stability-plasticity dilemma that is to say, the method that a brain or machine could learn fast about new objects and situation without suddenly being forced to forget previously learned, but still useful, memories. ART determine how to learn top-down expectations aim with attention on expectation of combinations of features, leading to a contemporary resonance that can operate quick learning. ART also predicts how large enough mismatches between bottom-up feature patterns and top-down expectations can turn a memory search, or hypothesis testing, for recognition categories with which to learn better to classify the world. ART thus defines a type of self-organizing production system. ART was practically demonstrated through the ART family of classifiers (e.g., ART 1, ART 2, ART 2A, ART 3, ARTMAP, fuzzy ARTMAP, ART eMAP, distributed ARTMAP), developed with Gail Carpenter, which has been used in large-scale applications in engineering and technology where fast, yet stable, incrementally learned classification and prediction are needed (Heins and Tauritz, 1995). Due to the function of ART, the feature is based on the relation of the brain and consciousness, in this research we consider to utilize this algorithm for brain-inspired method to regulate and perform the EI system.

In this part, we introduce and explain the information of ART that is applied in this research that consists of the basic algorithm of ART and the applied algorithm that implement in the robot system. With the reason that we select this method to implement in this system, since the method has basically ability to perform regarding a cognitive and neural theory of how the brain autonomously learns to categorize, recognize, and predict objects and events in a changing world. In addition, the method defines arbitrary intersections between processes of consciousness, learning, expectation, attention, resonance, and synchrony during both unsupervised and supervised learning.

4.3.1 **Adaptive Resonance Theory 1**

Firstly, for simplifying the knowledge of ART in this system, we would like to explain of the convention ART1 that is fundamental of this algorithm. ART-1 net is stable at any stage of learning because patterns at the last stage of processing are assigned to a particular cluster and seldom oscillate among different clusters. ART-1 net has the ability to equally learn (adapting to changing inputs) a previously untrained pattern at any stage of processing which resembles with the computational corollary of biological model of neural plasticity. The robot has to take decision on its next direction of movement based on online inputs where it has to process a set of input sensor readings.

Following computational steps give a more details on the above mentioned processing stages of the ART-1 net. The symbols used in the following algorithm have their own meaning as mentioned. The 'n' is the number of components in input training pattern ('S'); 'm' is the maximum number of cluster units that can be formed; 'q' is the vigilance parameter (set between 0 and 1); 'L' represents learning trials; 'b_{ij}' is the bottom-up weight from $F1$(b) layer to $F2$ layer; 't_{ji}' is the top-down weights from $F2$ layer to $F1$(b) layer; 's' is the binary input vectors comprising of the input components $s1, s2, \ldots, s_n$; 'x' represents activation vector for $F1$(b) layer; '$||x||$' represents norm of vector 'x' and is defined as the sum of components of 'x_i' where $i = 1, 2, \ldots, n$. For more description, the application of the following steps to robot navigation has been given in later sections.

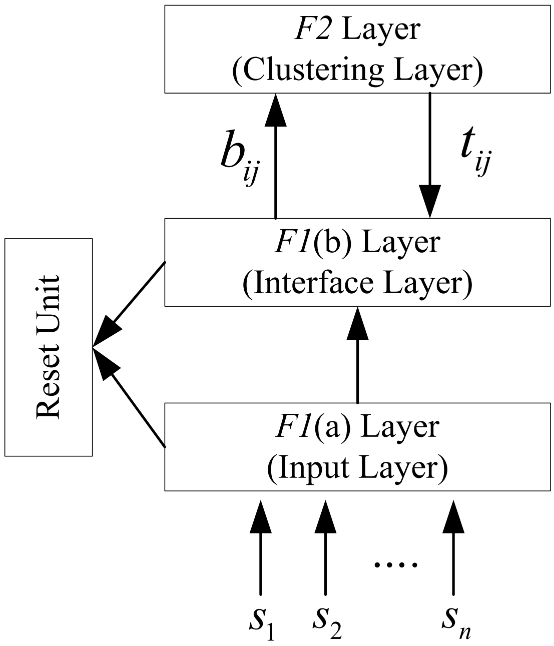


Fig. 4-8 ART-1 architecture model network.

Let beginning for the sequence of the algorithm,

- Step 1: Initialize all the parameters L > 1 and $0 < \rho \le 1$, then the weight initialization of ART-1 net with the equation (1)(1)(1) where $t_{ji}(0) = 1$.

$$0 < b_{ij}(0) \le \frac{L}{L - 1 + n} \tag{1}$$

- Step 2: Repeat step 3 to step 13 when stopping condition is false.
- Step 3: Repeat step 4 to step 12 for each learning input.
- Step 4: Set activation of all $F2$ units to zero. Set the activation of $F1$(a) units to input vectors.
- Step 5: Determine the norm of s using equation (2)
- Step 6: Send input signal form $F1$(a) layer to $F1$(b) layer using equation (3).

- Step 7: For each $F2$ node that is not inhibited, the following condition should hold: if $y_i \neq -1$ then calculate equation (4).

- Step 8: repeat step 9 to step 12 when reset is true.

- Step 9: Find J such that $y_j \geq y_i$ for all nodes j= 1, 2, 3,…, m. If $y_i = -1$, then all the nodes are inhibited and the current input patern cannot be clustered into $F2$ layer.

- Step 10: Determine again anticipation of each input in 'x' of $F1$(b) using equation (5). Where each weight vector 't_i'contains 'm' weights, and i = 1,2,3,…,n.

- Step 11 : Determine the norm of vector 'x' using equation (6).

- Step 12 test for the reset condition. If $\frac{\|x\|}{\|s\|} < \rho$, then inhibit node J, y_j=-1 and return to step 8. However, if $\frac{\|x\|}{\|s\|} \geq \rho$, then ART-1 leaning occurs, proceed to step 13 for weight updating.

- Step 13: update weights corresponding to node J using (7) and (8).

- Step 14: Test for the end of condition. The end condition would be one of the following: 1) no change in weights, 2) no reset of units; or 3) maximum number of epoch reached.

$$\|s\| = \sum_{i=1}^{n} s_i \tag{2}$$

$$x_i = s_i \tag{3}$$

$$y_i \neq \sum_{i=1}^{m} b_{ij} x_i \tag{4}$$

$$x_i = s_i t_i \tag{5}$$

$$\|x\| = \sum_{i=1}^{n} x_i \tag{6}$$

$$b_{ij} = \frac{L x_i}{(L - 1 + \|x\|)} \tag{7}$$

$$t_{ji} = x_i \tag{8}$$

For algorithm for ART1 that is the fundamental and normally for operating with the discreet data. However, this method would be the basic step for the evolutionary of ART. By this explanation that would rest the understanding of the concept of ART. The next, we would explain the fuzzy ART that is the basic and primary method in Topological ART.

4.3.2 **Fuzzy ART**

Fuzzy Adaptive Resonance theory is a supervised learning algorithm for both analog and binary data. The strength of prediction or recognition in Fuzzy ART can be varied using vigilance parameter. The algorithm has a vigilance parameter, which is dimensionless and is the criterion for an acceptable match. The vigilance parameter will be in between zero and one. The vigilance threshold sets the granularity of clustering. It also quantifies the amount of attractions of each type. A lower vigilance parameter would outcome in a larger cluster or category that will be not precise. High vigilance would influence to smaller and several pieces of categories. The vigilance threshold can be change to get different degrees of prediction. The basic Fuzzy ART structure is used for overlapping community detection is shown in Fig. 4-9. The comparison stage layer takes the input (one-dimensional array of values) and uses it to find the disjoint communities. The prediction stage accommodates the input values from input as well as from comparison stage. We modified the Fuzzy ART structure in such a way that the comparison field and prediction field takes different network measures which will help in predicting the community structure.

Basically, the algorithm is similar to the basic ART that consists of the two major layer $F1$ and $F2$. The inputs namely edge betweenness and Betweenness centrality are fed into the F1 layer that is known as the comparison stage in Fuzzy ART. The processed information from comparison stage layer is compared with the vigilance parameter. The processed output from comparison stage layer is the list of all communities in the online social network. This roll includes all disjoint communities in the social network. We have designed the Fuzzy ART framework in such a way that the output from the first layer (F1) can be used as a technique to find disjoint communities or non-overlapping communities. The second stage is named as prediction stage or F2 layer. The input to this layer consist of pair betweenness, betweenness centrality and community list (CL). The community list is the output of the F1 layer while pair betweenness and betweenness centrality are taken from the initial input.

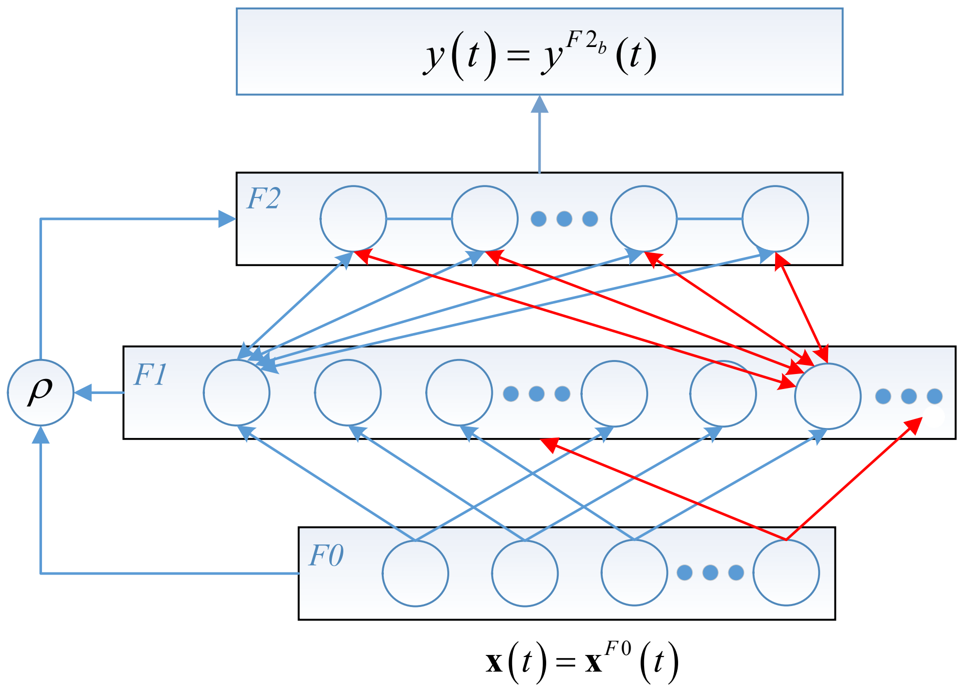


Fig. 4-9 Fuzzy ART network architecture

Fuzzy ART (Carpenter et al., 1991) organizes a calcualation from fuzzy set theory into ART network. By represented the crisp (non-fuzzy) intersection operator (∩) that describes ART 1 dynamics by the fuzzy AND operator ($\wedge$) of fuzzy set theory, fuzzy ART can train a stable categories in response to either continuous or discrete patterns or value. For the algorithm step, beginning from $F0$ represents the node of instant input vector; a layer $F1$ that obtains both bottom-up input from F0 and top-down input from a layer $F2$ that F2 stand for the active pattern, or category. In addition, vector **I** denotes $F0$ activation; vector **x** denotes $F1$ activity; and vector **y** denotes $F2$ activity. In weight vector that associated with the nodes memory in layer $F2$, let j denotes each node and w_j is the weights that can update, which compare according long-term memory (LTM) traces. Initially, the weigh will begin as $\omega_{j1}(0) = ... = \omega_{jM}(0) = 1$. For notification of parameters, a choice parameter as $\alpha > 0$, a learning rate parameter $\beta \in [0, 1]$, and a vigilance parameter $\rho \in [0,1]$ use to determine fuzzy ART dynamically. Category choice for each input **I** and $F2$ not j, the choice function T_j is defined by equation (9). Where the fuzzy intersection $\wedge$ is define by equation (10) (Zadeh, 1965) and where the norm $|\cdot|$ norm is assigned by equation (11).

The system makes a category choice when at most one $F2$ node can become active at a given time. The index J denotes the chosen category, where equation (12) when the J^{th} category is chosen, y_j =1; and y_i = 0 for $j \neq J$.

For the weight modification of resonance case of reset case, resonance occurs if the match function $|\mathbf{I} \wedge \mathbf{w}_j| / |\mathbf{I}|$ of the chosen category meets the vigilance criterion as equation (13). Learning then ensues, as defined below in equation (14). Otherwise if mismatch reset happen, where the value of the choice function T_J is set to 0 for the duration of the input presentation. The search process continues until a chosen category that J satisfies the matching criterion in equation (13). In training, when search ends, the weight vector $\mathbf{w}_j$ learns according to the equation (14).

Fast learning that corresponds to set $\beta = 1$. Using the fast learning and slow recoding option, we set $\beta = 1$ when J is an uncommitted node and take $\beta < 1$ after the category is committed. Then, Normalization by complement coding, Normalization of fuzzy ART inputs prevents category proliferation. The complement coded $F0$ to $F1$ input **I** is the 2M-dimensional vector as (15) where the restriction as equation (16) a complement code in is automatically normalized, as equation (17). With complement coding, the initial condition in equation (18) will replace in the fuzzy ART to initial condition as the weight associated layer $F2$.

$$T_j(\mathbf{I}) = \frac{|\mathbf{I} \wedge \mathbf{w}_j|}{\alpha + |\mathbf{w}_j|} \tag{9}$$

$$(\mathbf{p} \wedge \mathbf{q})_i \equiv \min(p_i, q_i) \tag{10}$$

$$|\mathbf{p}| \equiv \sum_{i=1}^{M} |p_i| \tag{11}$$

$$T_J \ = \ max\{Tj \ : j = 1 \ldots N\} \tag{12}$$

$$\frac{|\mathbf{I} \wedge \mathbf{w}_j|}{|\mathbf{w}_j|} = \geq \rho \tag{13}$$

$$w_J^{(new)} \ = \ \beta(\mathbf{I} \wedge \mathbf{w}_J^{(old)}) + (1-\beta)\mathbf{w}_J^{(old)} \tag{14}$$

$$\mathbf{I} \ = \ \left(\mathbf{a}, \ \mathbf{a}^c\right) \ \equiv \ \left(a_1, \ldots, a_M, \ a_1^c, \ldots, a_M^c\right) \tag{15}$$

$$a_i^c \equiv 1 - \alpha_i \tag{16}$$

$$\mathbf{I} \ = \ \left|\left(\mathbf{a}, \ \mathbf{a}^c\right)\right| = \sum_{i=1}^{M} a_i + (M - \sum_{i=1}^{M} a_i) = M \tag{17}$$

$$\omega_{j1}(0) \ = \ \ldots = \ \omega_{j,2M}(0) \ = \ 1 \tag{18}$$

4.3.3 **Topology learning of hierarchical ART**

For the related or tradition offline-learning outlook with training algorithm, verification and test process are not sufficient in the real-world data that is with large noise variance and imbalance. This research thus investigate the approach that can handle those problems. As mentioned problem, the incremental network and on-line learning have gotten a lot of interested recently since such machine learning technology are needed to systematically complete information that can succeed a solution to adapt and apply into a non-stationary system. Adaptive resonance theory and topology-based (Tscherepanow, 2011) that call TopoART, was developed a topological structure for unsupervised learning using Fuzzy ART. Using TopoART algorithm a stable representation of the data is created. The model was used for clustering and learning for imbalance, noisy and robust information that is suitable for the practical data since the robot is the system that associate with the dynamic interaction with the surrounding environment such human, interesting object and some necessary service task.

For archiving the topology learning network using ART, TopoART provides this capability to construct or learn the model based on the dataset that also the one of the neural network which difference the usual because the ART considers about resonance state. From its conventional ART, it acquires the sense of fast and stable on-line learning using expectations phrase (categories). However, the categories are additionally added by edges matching the topology of the input distribution enabling the formation of arbitrarily shaped clusters. The typical network model and the algorithm of TopoART are highly compared to Fuzzy Art (Carpenter et al., 1991) an efficient ART network utilizing rectangular categories for matching input learning. There are three layers of the neural network in Fuzzy ART that consist of complementary input converting layer, comparison layer, and recognition layer.

In this system, we utilize TopoART due to the benefit, which is applied for the system of Emotional Intelligence. By this implementation the robot can have the inside state variance of affective as human which the complex biology. In this method, we utilize the TopoART based on the CBA system that can let the old system getting approach in high level of the consciousness level. Because the previous system of the CBA can perform only in the level three. The proposed will let the robot get beginning by having the inside state affective and brain-inspired system for EI the robot will have more sophisticated feeling and emotion that should persuade for complex behavior as human. The next section, we will describe the methodology that we combine TopoART and CBA to perform for the EI system.

4.4 Emotion intelligence using TopoART-R

As noted above, the robot's facial expressions are based simply on the motivation. In human society however, etiquette and manners must also be considered. A robot must therefore perceive the humans' emotional expressions in accord with etiquette and manners in order to engage in communication that does not create friction or conflict with humans (Pennebaker et al., 2001). In the system we describe herein, the robot would not only express emotions; it will regulate its feelings by sharing its feelings with the user, and then express the appropriate emotion. Fig. 4-10 shows the model of emotional regulation using TopoART-R, which is based on the regression model that we used to determine the intensity of the emotion.

Table 4-1. Normalized intensity depending on basic emotions

Fundamental	Intensity value
Surprise	0.8
Pleasure	0.7
Hope	0.6
Neutral	0.5
Fear	0.4
Sadness	0.3
Disgust	0.2
Anger	0.1

For example, when the regulated emotion is happiness, we can also acquire the intensity of the feeling of happiness regarding perception when the user's and robot's emotions differ, and the output of the regression would calculate common the intensity of each fundamental emotion between the robot and user using basically averaging emotion. Since we divided the fundamental emotion by the level, for example, surprise is the maximum positive emotion, then pleasure, hope, neutral, fear, sadness, disgust and most negative is anger which are represented intensity value in Table 4-1. From this table we prepare the data sample for determine the expression of the robot when the robot perceives the human expression. The robot emotional expression would basically determine the output expression by calculating the average value of emotion between robot emotion and the emotion that human expressing. The value of emotion used to calculate, depends on Table 4-1. These emotional value would apply for determination of the emotional generation and expression system of the robot which is based on human emotional expression and robot inside-state emotion. With the EI model, we constructed the model by first training shared emotions between the user and the robot, so that the robot will begin to learn the relationship between the user and the robot. The training dataset for sharing emotion model is shown in **Error! Reference source not found.**. We used Plutchik's model of emotion for the construction of the emotion structure and the relationship of expression (Plutchik, 1980, p. 198). For operation in the practical world, we applied the EI module using TopoART-R, which is an online machine learning method used in situations in which dynamic operation-adaptation to new patterns benefits an autonomous proper-learning-based society and a robot's owner.

Table 4-2. The robot expression determination based on human emotional expression and robot inside-state emotion

User / Robot	Anger	Disgust	Sadness	Fear	Neutral	Hope	Pleasure	Surprise
Anger	Disgust	Disgust	Disgust	Sadness	Sadness	Fear	Fear	Neutral
Disgust	Disgust	Disgust	Sadness	Sadness	Fear	Fear	Neutral	Neutral
Sadness	Disgust	Sadness	Sadness	Fear	Fear	Neutral	Neutral	Hope
Fear	Sadness	Sadness	Fear	Fear	Neutral	Neutral	Hope	Hope
Neutral	Sadness	Fear	Fear	Neutral	Neutral	Hope	Hope	Pleasure
Hope	Fear	Fear	Neutral	Neutral	Hope	Hope	Pleasure	Pleasure
Pleasure	Fear	Neutral	Neutral	Hope	Hope	Pleasure	Pleasure	Surprise
Surprise	Neutral	Neutral	Hope	Hope	Pleasure	Pleasure	Surprise	Surprise

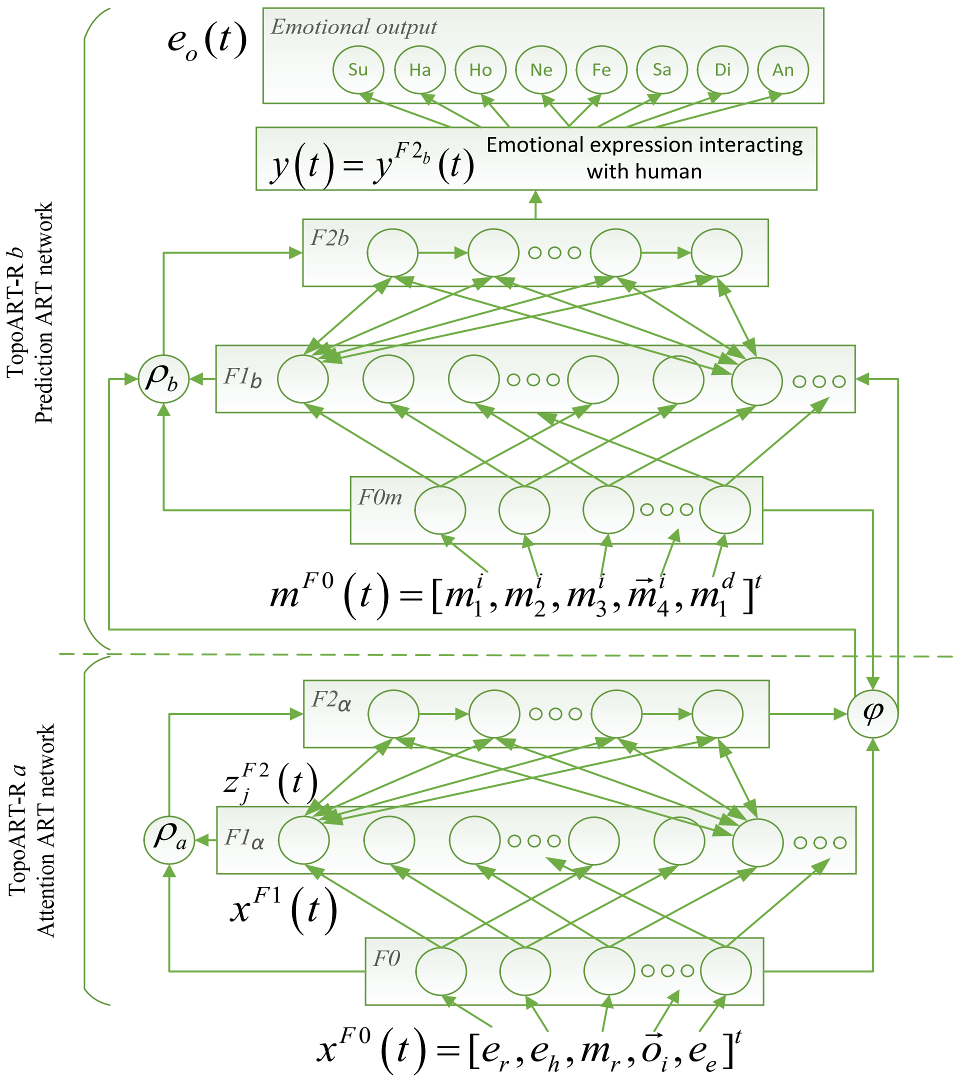


Fig. 4-10 The model of emotional regulation using TopoART-R.

For training TopoART, during training, we used the independent variables of robot cognitive parameters, which are comprised of robot emotion e_r, human emotion e_h, robot motivation m_r, the vector of appearing objects at the pixel ratio $\mathbf{o}_i$, and the emotional expression variable e_e which is the label output; these are treated in the same way in Eq. (4-20). For the occurrence of time t, the corresponding input and output label parameters are conjoined and then fed as input $\mathbf{x}^{F0}(t)$ into the TopoART-R a network.

From the $F0$ layer, the input vectors $\mathbf{x}^{F0}(t)$ are also determined with complementary coding according to fuzzy logic. In each parameter of an input, vector $\mathbf{x}^{F0}(t)$ is represented as a number between 0 and 1 by Eq. (4-21). From the $F1_a$ layer to the $F2_a$ layer, vectors $\mathbf{x}^{F1}(t)$ are fed and activated by Eq. (4-22), whereby $|...|_1$ denotes the city-block norm, and $\wedge$ denotes an element-wise minimum operator. The activation function determines the similarity by $\mathbf{x}^{F1}(t)$ and the set of neurons by j. The weight $w_j^{F2_a}(t)$ represents spanning hyper-rectangular networks. From the $F2$ layer, the node, which is the most similar, activates the best-matching node bm by the matching function in Eq. (4-23).

In accord with the online learning, the TopoART-R a achieves resonance, and $\mathbf{w}_{bm}^{F2_a}(t)$ is determined as the next step by using Eq. (4-24). The second matching function is provided as necessary by Eq. (4-25), in which sbm denotes the second best match node applied to weight vector $\mathbf{w}_{sbm}^{F2_a}(t)$. The matching function can also be enhanced for handling the noisy data of input space in batch learning, those are always online training. As in the ART, which includes a vigilance parameter, TopoART *a* and *b* define the vigilance parameter determined by Eq. (4-26).

$$\mathbf{x}^{F0}(t)=[e_r(t),e_h(t),m_r(t),\mathbf{o}_i(t),e_e(t)]^T \tag{4-20}$$

$$\mathbf{x}^{F1}(t)=[e_r(t),e_h(t),m_r(t),\mathbf{o}_i(t),e_e(t),1-e_r(t),...,1-e_e]^T \tag{4-21}$$

$$z_j^{F2_a}(t)=\frac{\left|\mathbf{x}^{F1}(t)\wedge\mathbf{w}_j^{F2_a}(t)\right|_1}{\alpha+\left|\mathbf{w}_j^{F2_a}(t)\right|_1}\quad,\alpha>0 \tag{4-22}$$

$$\frac{\left|\mathbf{x}^{F1}(t)\wedge\mathbf{w}_{bm}^{F2_a}(t)\right|_1}{\left|\mathbf{x}^{F1}(t)\right|_1}\quad,\alpha>0 \tag{4-23}$$

$$\mathbf{w}_{bm}^{F2_a}(t+1)=\mathbf{x}^{F1}(t)\wedge\mathbf{w}_{bm}^{F2_a}(t) \tag{4-24}$$

$$\mathbf{w}_{sbm}^{F2_a}(t+1)=\beta_{sbm}(\mathbf{x}^{F1}(t)\wedge\mathbf{w}_{sbm}^{F2_a}(t))+(1-\beta_{sbm})\mathbf{w}_{sbm}^{F2_a}(t) \tag{4-25}$$

$$\varrho_b=\frac{1}{2}(\varrho_a+1) \tag{4-26}$$

For the prediction of the robot's emotion output, the instant parameter input obtained from the robot operation overtime will feed into the constructed TopoART-R of the emotional intelligence model. For real-world data, the information is noisy and incomplete, relating the robot sometimes the input data not complete such losing some objects information or not include the unknown data because the amount of the entire data in practice is too large. The algorithm therefore designs the parameter for indicating the incomplete data omitting the missing parameters. In Eq. (4-27), this describes the masking function for $\mathbf{x}^{F0}(t)$ by $\mathbf{m}^{F0}(t)$ where $m_1(t)$ to $m_5(t)$ indicate $e_r(t), e_h(t), m_r(t), \mathbf{o}_i(t)$ and $e_e(t)$, respectively. Finally, the determined expression of emotional intelligence of the TopoART-R is a simple majority vote the output of emotional expression by Eq. (4-28).

$$\mathbf{m}^{F0}(t)=[m_1(t),m_2(t),m_3(t),\mathbf{m}_4(t),m_5(t)]^T \tag{4-27}$$

$$e_o(t)=\mathrm{argmin}_{k\in 1,\ldots,8}\mathrm{d}(y(t),e_k) \tag{4-28}$$

For the output of the emotional intelligence using TopoART-R, the robot is equipped this method to create the inside state of robot emotion when the robot is stimulated from the environment, or by human expression, or by self-stimulation from the memory. Fig. 4-11 presents the example of various emotional inside-state factors depending on the cognitive or perception. Fig. 4-12 illustrate the level value of inside state of various emotion at instant time when the robot perform the emotion generating system depending on the recognition of object or human expression. In this figure the robot has the maximum emotion of fear. In addition for complex emotion the robot has a slightly neutral and sadness that is from the cause of the memory of some perception system regarding the sadness and neutral is remaining.

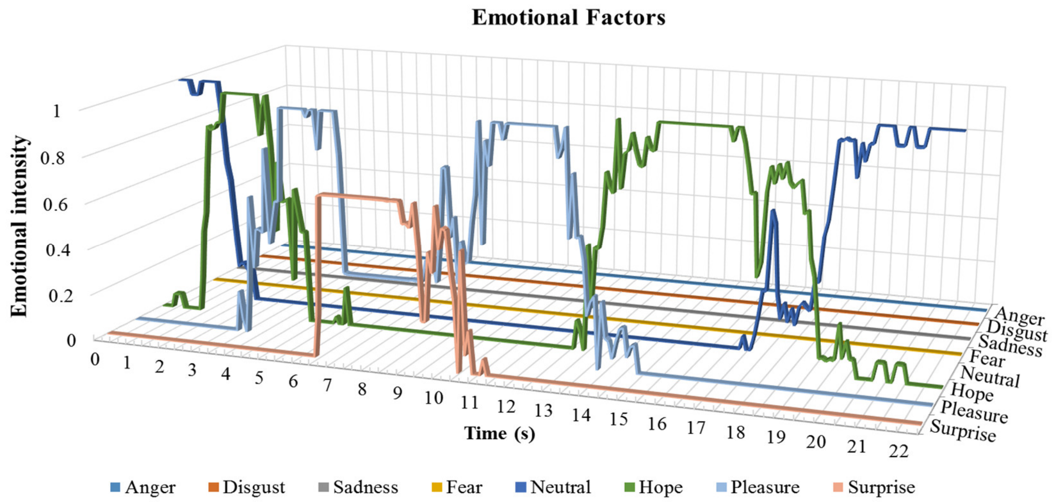


Fig. 4-11 Output (emotional intensity depending on basic emotion that mean inside affective state) of eight emotional factors from TopoART-R.

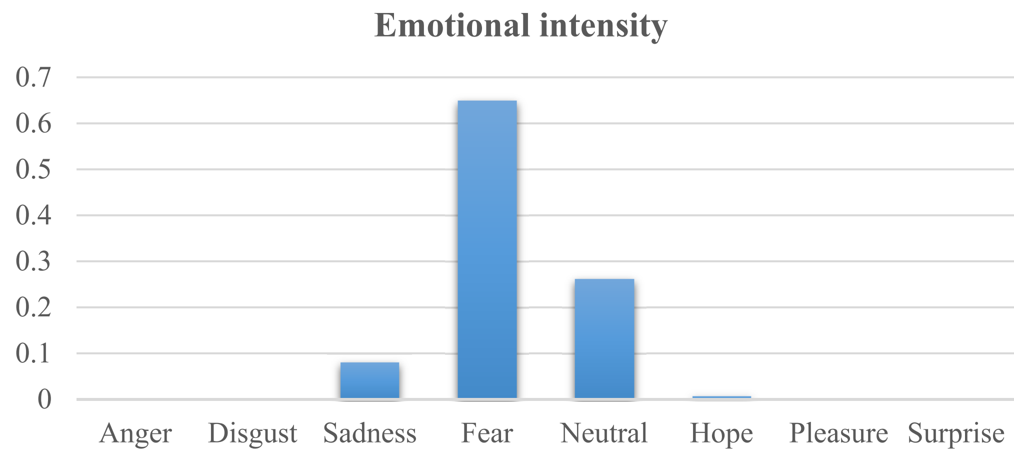


Fig. 4-12 Inside state of emotion variables at instant time.

In this example, the robot recognizes a favorite object, and then the affective factors of hope, pleasure and surprise each increase. As shown in this system, more than one emotional factor occasionally occurs at the same time, but there is only one highest-intensity emotion, which is expressed to the external world. The system is designed to provide a compound emotional system similar to that of humans by providing the inside emotional system using eight dimensions that follow the basic emotions in Plutchik's model (Plutchik, 1980). Accordingly, this emotion generating system also apply by considering with the psychological view of plutchich's wheel of emotion that he propose the emotional space by the eight emotions. By our system that can apply to this psychological view, the robot can have unlimited emotion depending on the emotional intensity. Also there is the complex emotion occur when pairs of adjacent emotion combine for example love is combination of joy and trust as shown in Fig. 4-13. However currently that is difficult to the robot define the whole emotion which can occur in human mind represented by compound or complex emotion exactly. But in the future this information should be useful if the robot can learn more experience, event and having more sensational field.

In humans, there are varying and distinct forms of happiness that depend on the individual's personality, memory and experience and the event that cause affective information because the human provides the high amount of sensation felid and memory based on the biology structure. Therefore, in the robot that can conscious the basic emotion and has non-conscious affective information which is small intensity of inside state of emotion from the set of basic emotional factors (Talarico et al., 2004; Walla and Panksepp, 2013).

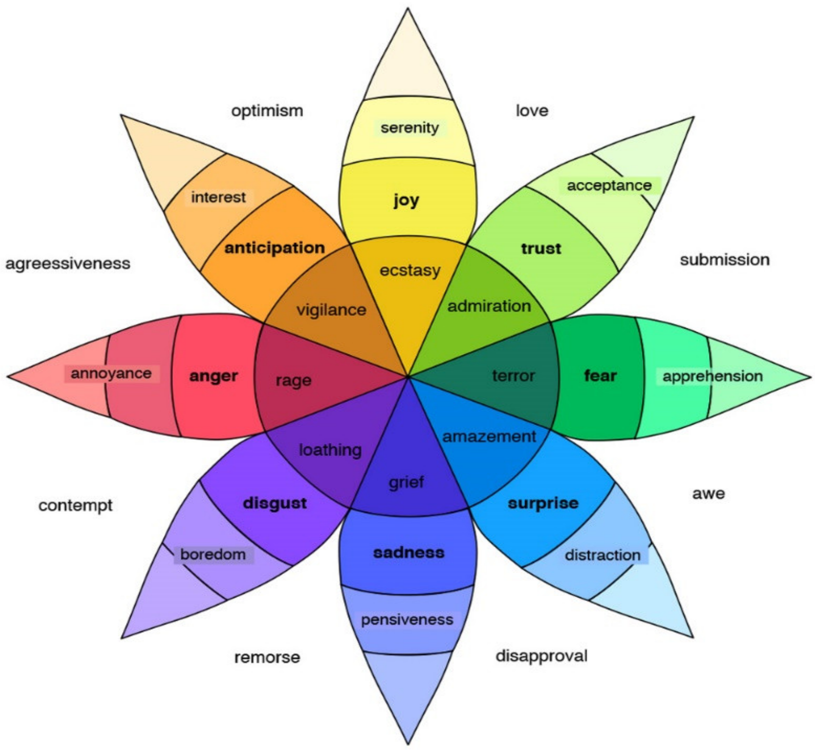
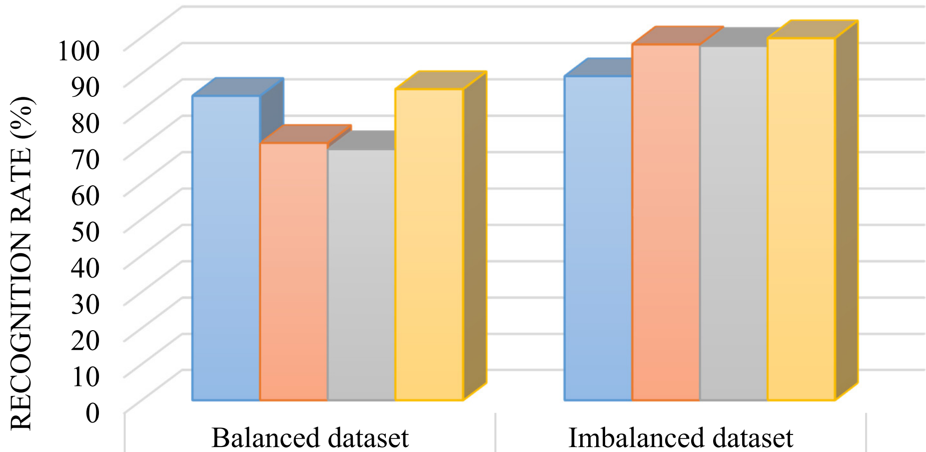


Fig. 4-13 The emotion wheel of Plutchik model.

Regarding the performance of the learning methods, we experimented and process the comparison of the performance of TopoART-R with those of the related methods SVM, Rectangular SOM, and Hexagonal SOM. That is to investigate the difference, performance and the feature of the method that is to decide the great one based on our emotion generating system. The system is tested with information with our robot system generating the emotion from predefined of the criterion of emotion when the motivation and the cognitive parameter are the dataset of input.

Firstly, we use an SVM with the Gaussian Radial Basis Function kernel based on a quadratic loss multi-class model (Guermeur and Monfrini, 2011). For SOM, we compared the SOM topology of rectangular and hexagonal models with the assigned parameters such as a 30×30 map size, a 0.05 learning rate, and 50,000 epochs (Kohonen, 1982, p. 198). For preparing the learning dataset, we used a sample of the pattern of cognitive parameters of the CONBE robot in which the input of the dataset consists of the motivation, the differential motivation, and the factors of color recognitions of red, green, blue and flesh. The dataset was labeled with the output from eight emotions: surprise, pleasure, hope neutral, fear, sadness, disgust, and anger. We then separated two groups of the dataset: (1) the balanced dataset for training, which provided a small quantity of 1,200 samples, and (2) the imbalanced dataset, which is the larger dataset of 5,076 samples. For the balanced dataset for training, the experiment test was conducted with a testing dataset from 5,000 samples, which are not included in the training dataset. For the imbalanced dataset, we used these samples to be tested. The results of the performance of these methods are shown in Fig. 4-14. Therefore we suggested the TopoART-R to develop of this system in the thesis compared with the performance and outstanding from the conventional system.



	Balanced dataset	Imbalanced dataset
SVM	83.9	89.3
Hex SOM	70.96	98.04
SOM	69.26	97.63
TopoART-R	85.75	99.74

Fig. 4-14 The CONBE robot’s performance (i.e., recognition rate) of the learning methods (SVM, Hex SOM, SOM, and TopART-R) when using the balanced dataset and imbalanced dataset.

We observed that among the learning processes, TopoART-R performed outstandingly, and we therefore decided to use TopoART-R in the CONBE robot. Since TopoART-R is based on the ART method, it was developed considering cognitive and neural theories and is also strongly related to the aspects of consciousness that are composed of the long-term and short-term memory and concerned stability-plasticity dilemma. We accordingly implemented the TopoART for the robot’s performance and the methodology that similarly refer to the biologically inspired cognitive process (Grossberg, 2013).

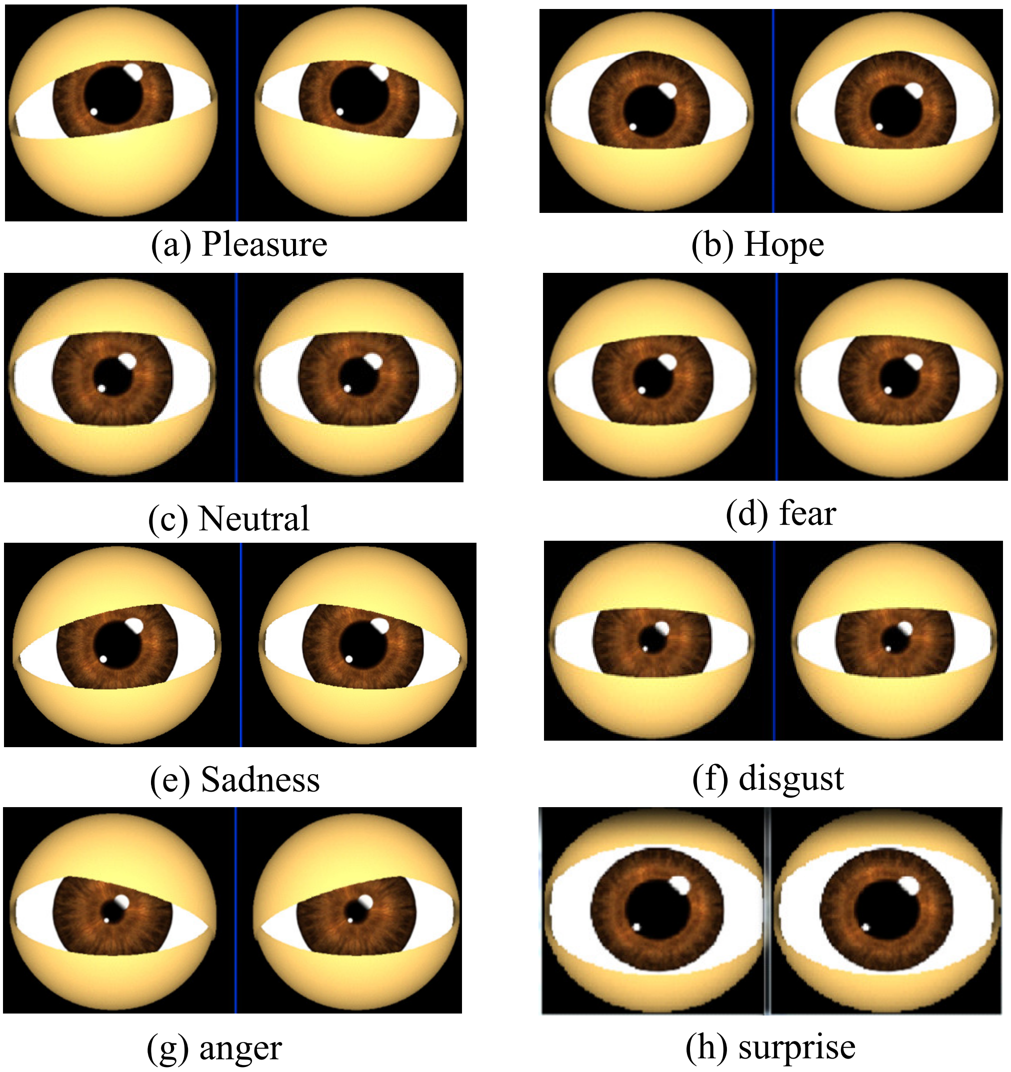


Fig. 4-15 The CONBE robot's eye expression for each emotion: (a) pleasure (b) hope (c) neutral (d) fear (e) sadness (f) disgust (g) anger and (h) surprise.

4.5 Robot's eye expression

To provide the CONBE robot with a way to express its 'emotions,' we supplied a small display in the head with the robot would express its emotion via its eyes, based on a 3D virtual eye software program. When the robot detects a user, the robot provides its motivational expression to interact with the user. We therefore simplified the emotional commands, thereby obtaining the decision for the expression. The robot's facial expression depends on its motivation intensity and the user's expression for mutual interactions between the user and robot. Fig. 4-15 shows the robot's eye expression for each emotion. For the expression of each emotion, we made the robot's eyes mimic the corresponding human expression based on prior research (Ekman, 2006; Hess, 1965).

4.6 Summary

In this chapter, the overview of the proposed system is thoroughly described that consist of three major processes: the empathic skill for human expression; later the methodology of emotional intelligence based on the on-line learning brain-inspired method TopoART that could let the robot can perform the consciousness and behavior in higher level in cognitive process; and finally emotional expression process. The CONBE robot in a realistic environment executes the proposed system. All experimental results including the effectiveness of the proposed system by dividing as various situation of experiment that will explain in the next chapter.

Chapter 5

Experiment and discussion

5.1 Experiment and results

In this section, we describe the CONBE robot's behavior and emotional expression in face-to-face emotional expression with humans. The experimental environment and configurations, which corresponded to an indoor situation, were prepared in our laboratory. The robot was arranged on a table with the height of the robot's head approximating human height. The experiment was begun using the behavior and recognition that are normally observed in pets such as dogs, and then when the robot could recognize the human, it provided the expressions reflecting its emotional intelligence by facial expression recognition and emotional generation. The robot also dynamically demonstrated the behavior of interacting with the object of interest, i.e., the human user.

We attempted the development a practical emotionally robot with the skills needed to engage in interactions with humans, which have been overlooked in recent research. The CONBE robot has affective skills based on the animal brain-inspired and consciousness process. In the present study, we tested the robot's overall intelligence, emotional responses, and the cross-communication between human users and the robot in order to determine the robot's effectiveness in a real-world environment.

The arm of CONBE robot could autonomously perform its behavior with CBA by using its 7-DOF manipulator and expressing its emotions based on the biologically inspired TopoART via the robot's face, and express the robot considered emotion based on EI. The experiment described here was composed of two main parts: (1) a test of the robot's pet-like behavioral and emotional expression, and (2) a test of the cross-communication interactions based on the robot's emotional intelligence.

For the robot's pet-like behavior and emotional expression, we observed the changes in the robot's actions and emotional expressions based on the transition of the robot's motivation, the synthetic dopamine, and the emotional factors. The robot was first stimulated by interesting objects in its environment. Fig. 5-1 shows the robot's response to three objects' movement along with the distance of each object that a red, green and blue line represents the distance of red, green and blue objects respectively.

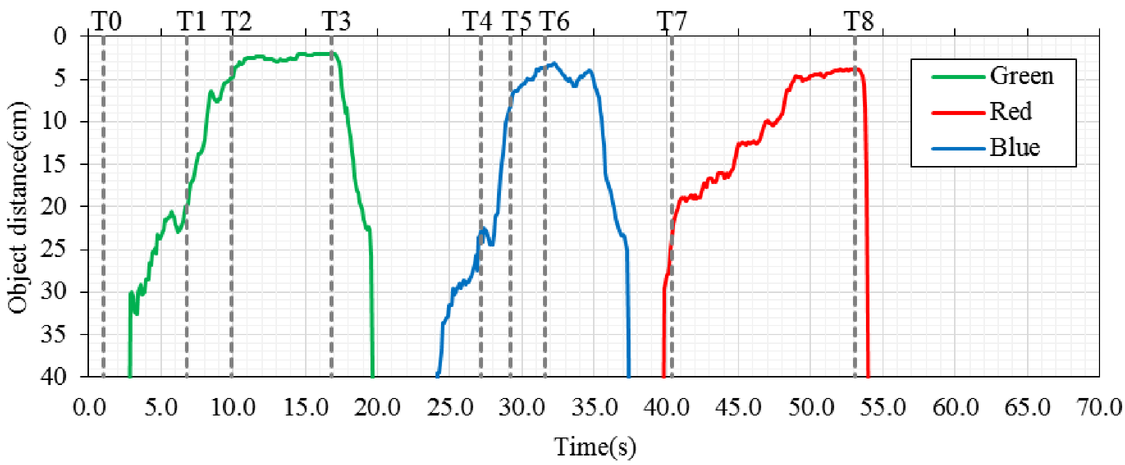


Fig. 5-1 The object stimulation of the robot during the experiment as the distance of the interested object stimulating the robot changed.

As the robot recognizes the object, the robot would release dopamine and show aroused motivation. As shown in Fig. 5-2, the robot's motivation is influenced as reflected in an animal-like model by and changes with the periods following each object's appearance. The robot is first interested in a newly presented object, and then it 'memorizes' each object, representing long-term memory by the dopamine. With the disappearance of an object, the dopamine of this object would become dim over time.

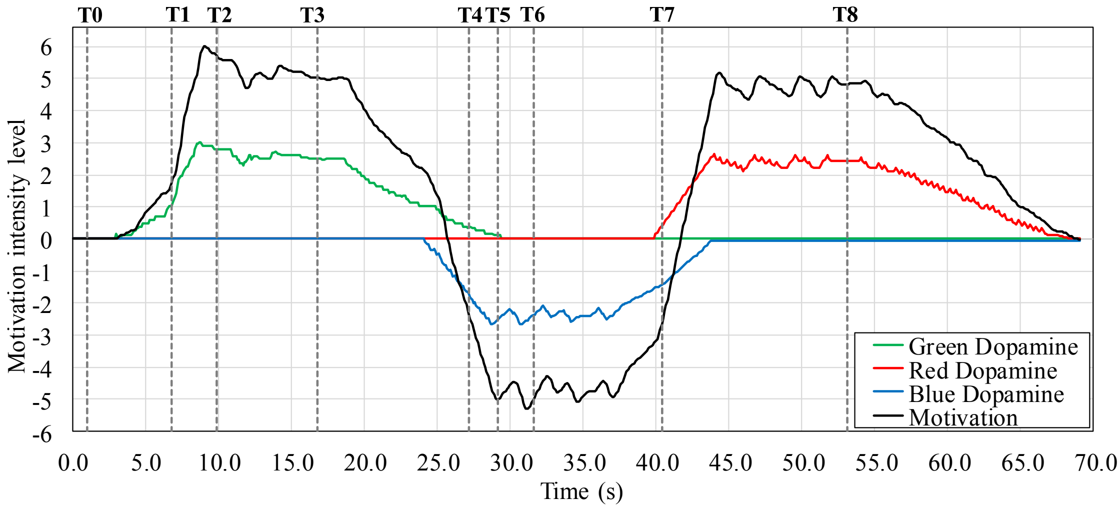


Fig. 5-2 The robot's motivation and behavior where T0-T8 represents the time when the robot is stimulated depending on the distance and appearance of the objects that mentioned above figure.

Fig. 5-3 shows the robot emotions, which were influenced by the motivation. We divided the behavior system's transitions into time periods from T0 to T8 described below. Fig. 5-4 shows capture images of the robot's motions during the experiment.

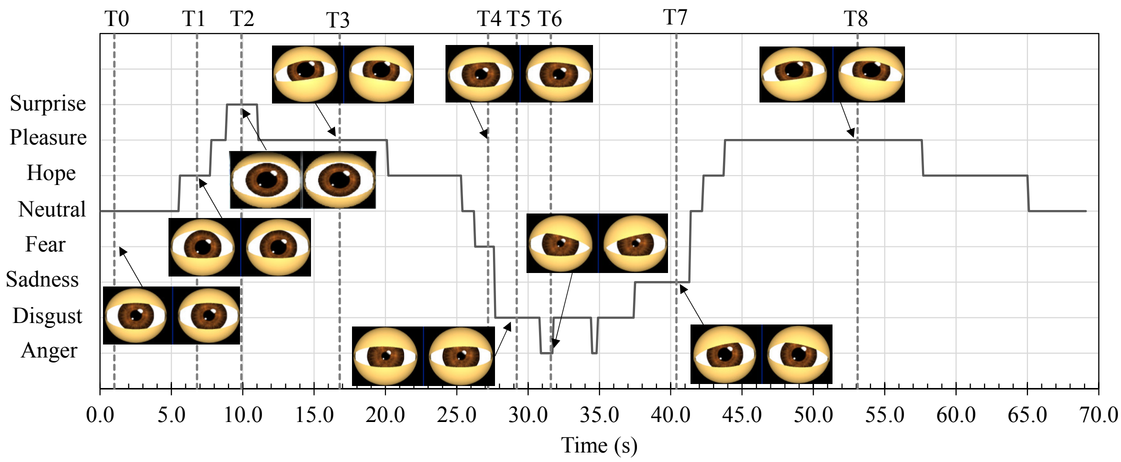


Fig. 5-3 The robot's emotional expression when interacting with an object.

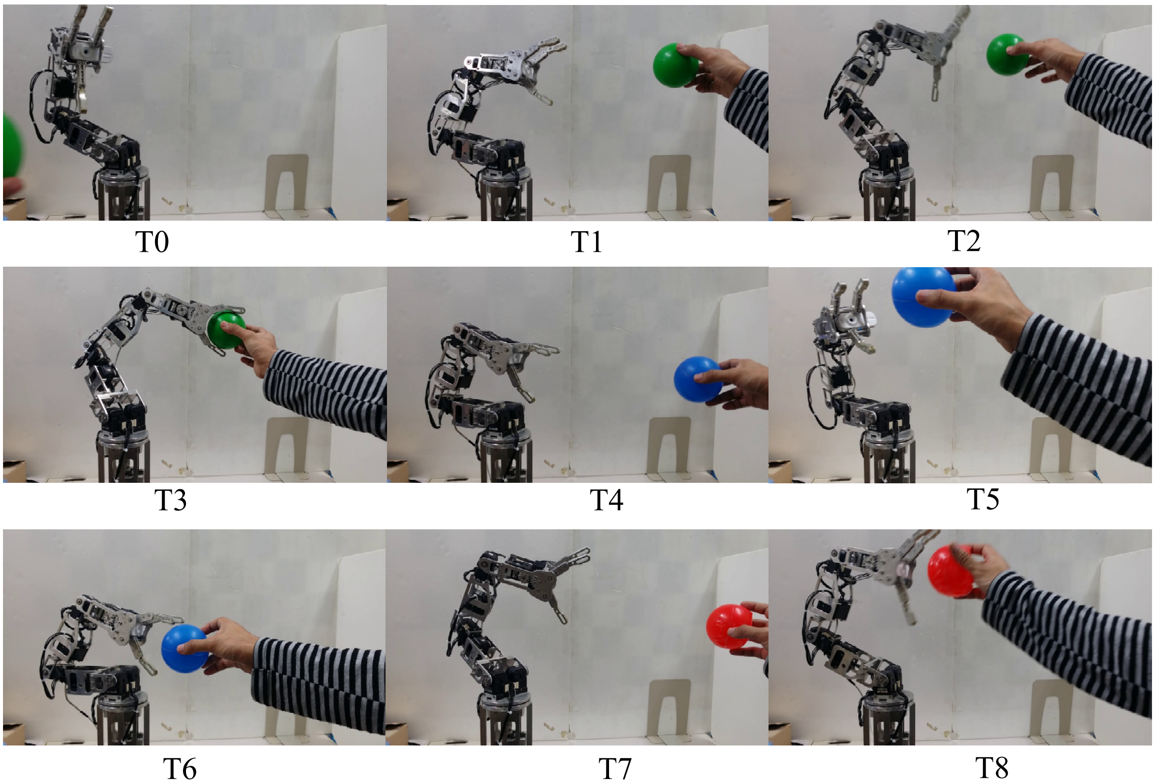


Fig. 5-4 The captured images of robot behavior when the robot recognizes object.

Beginning at T0, the robot expressed a neutral feeling because there was no object and the robot had no memory before it began to explore its environment, looking for an interesting object. During T0–T1, the robot recognized a green ball, which was its most favorite object, and thus the robot's motivation was stimulated. At that time point, the robot expressed the feeling of hope and made the action (behavior) of capturing the green ball.

At T2, the robot showed the emotion of surprise because the motivation rapidly increased and broke through the surprise level; at that time, the robot also showed it widest open mouth and approached to the ball. At T3, when the robot was near enough and caught the ball, it expressed pleasure. From T3 to T4, the robot could not recognize the green ball, and its motivation declined. Subsequently, a blue ball (a 'hated' object) was placed in the robot's environment, and the motivation then became negative; the robot looked at the ball and stayed away from it, with 'vigilance'.

At T4, the robot expressed fear of the hated blue ball. At T5, the robot showed the behavior of avoidance of the ball, but we brought the ball into the robot's view and then the motivation became more negative; the robot therefore expressed disgust. At T6, the robot moved quickly to avoid the ball, but we forcefully placed the ball in the robot's way; the motivation was then broken through as an aggressive emotion, i.e., anger. During T6–T7, the blue ball disappeared and the robot's motivation increased. At T7, the red ball began to appear in the robot's field of view, but there was still a memory of the blue ball represented by blue dopamine. The motivation was thus still negative, causing the robot to express sadness.

Later the motivation increased when the red ball appeared; the robot captured the red ball, but it was not keen to approach the ball because the red ball was not the most favorite object however it was still interesting and pleasure. At T8, we moved the red ball to a spot near the robot and the robot attempted to catch the ball and widely opened its mouth as an expression of pleasure.

For the second part of the experiment, i.e., emotional expression between the CONBE robot and a human user, we monitored the output of the robot's facial expressions, the robot's behavior, its emotion generation and its emotional expressions toward a human user. For the emotional generating system, we first extracted the facial feature parameters using the CLM to predict the emotional expression by the HMM. The human emotions and robot emotions were then used to consider the suitable emotional expressions, using the TopoART. The expression of a given emotion by the robot was determined based on the sharing of an emotion between the human and the robot, where the expression is acceptable and does not leave the human unsatisfied. Fig. 5-5 shows how the dopamine levels changed in accord with the emotional motivation based on the neurotransmitter dopamine of each object during testing. Fig. 5-6 illustrates the changes in the robot emotion, human emotion and their expression throughout the task period. Fig. 5-7 shows the captured FER images with the robot's and human's expression from T0 to T5.

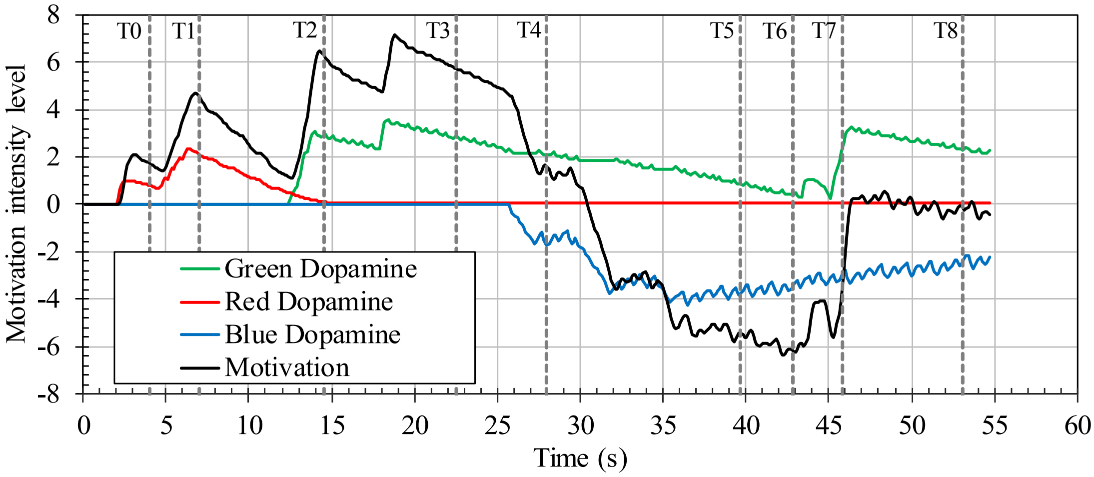


Fig. 5-5 The results of the various levels of dopamine in accord with the robot motivation when it interacted with a user in an emotional expression.

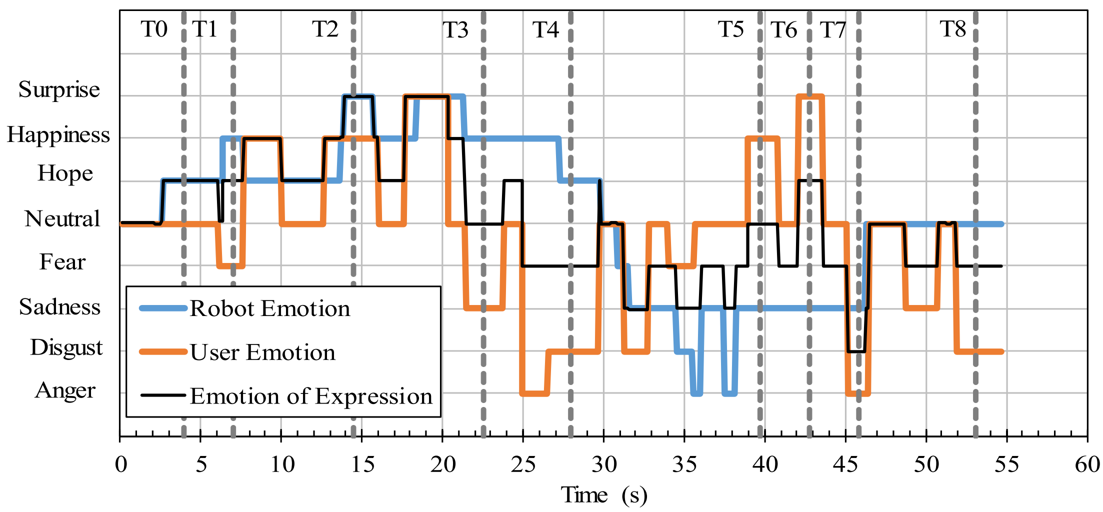
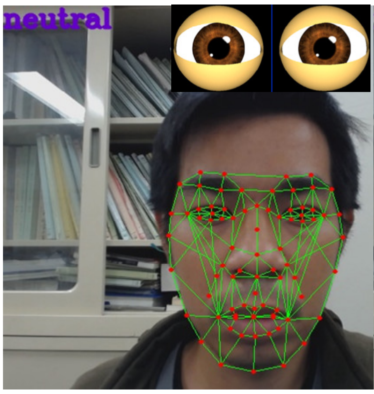


Fig. 5-6 The results of the intelligence emotional expression during the interaction with a human user.

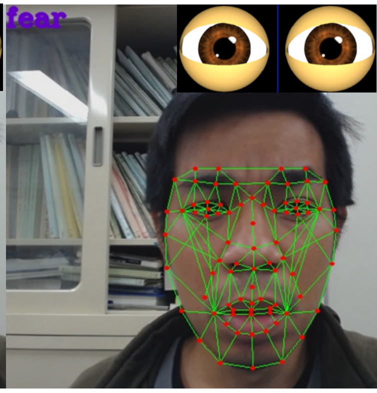
At the beginning of the experiment, the robot 'felt' neutral and expressed neutrality as its motivation was not stimulated; when the favorite red object was recognized the robot's motivation started to increase. At T0, the robot felt hope in accord with the increasing motivation, and the human user expressed neutrality. The robot then expressed hope resulting from the encouraging human feeling. At T1, the robot expressed happiness as the motivation level stimulated a higher positive emotion, but the human expressed fear when the robot shared the user's affective feeling. The robot then expressed hope, which that also agrees with the manner sense.

At T2, the robot expressed surprise because it suddenly recognized the most-favorite object, i.e., the green ball, and the motivation level was high. The user expressed hope, and then the robot continues to express surprise because the hope and surprise emotions were not conflicting. At T3, the robot was happy, but the human expressed sadness, and then the robot expressed neutrality and masked its happiness due to its SI. At T4, the robot was hopeful, but the user expressed disgust the robot then expressed fear.

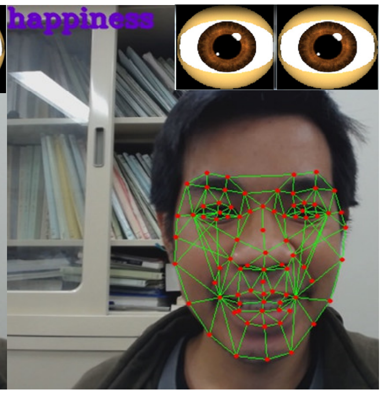
At T5, the robot was sad, but the human was happy; the robot then expressed neutrality and masked its sadness due to its SI and emotion sharing. At T6, the robot was sad, but the user expressed surprise; the robot pretended to feel hope following the human's surprise, which is a strongly high-positive emotion. At T7, due to the emotion sharing, the robot was sad and the human was angry, and then the robot expressed disgust. Finally, at T8, during a decrease in the green dopamine level and as the level of negative blue dopamine dropped, the motivation oscillated around the neutral level. The robot accordingly felt neutral but the user expressed disgust. The robot then expressed fear because the user's emotion affected the robot.



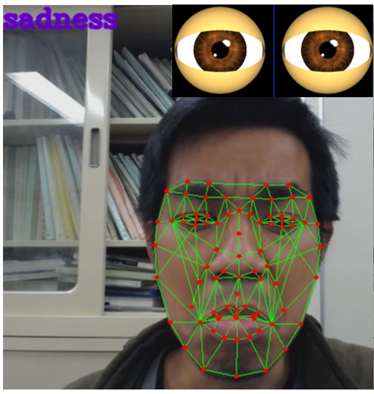
T0) Robot expression: Hope
User expression: Neutral



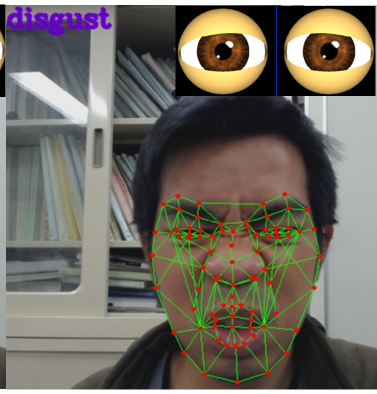
T1) Robot expression: Hope
User expression: Fear



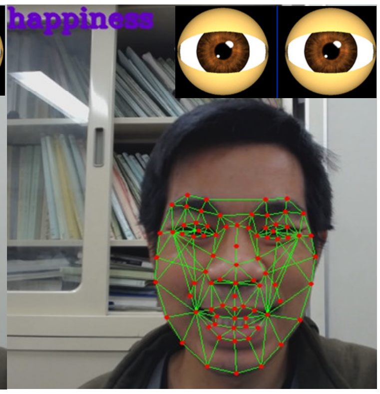
T2) Robot expression: Surprise
User expression: Pleasure



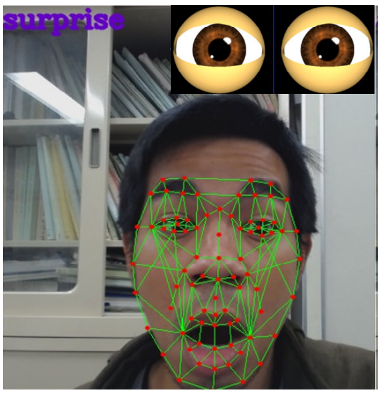
T3) Robot expression: Neutral
User expression: Sadness



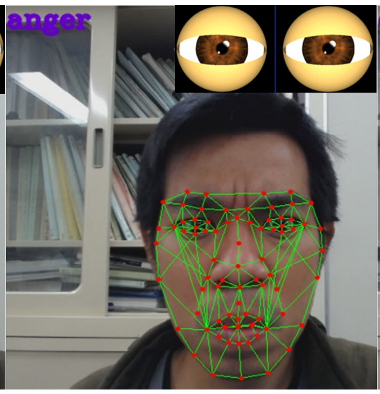
T4) Robot expression: Fear
User expression: Disgust



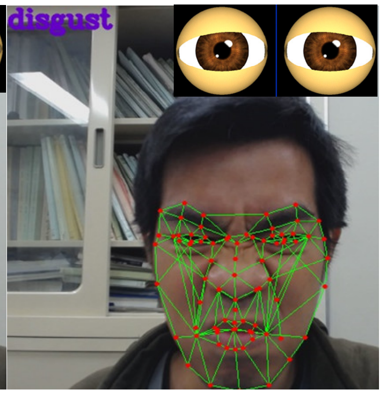
T5) Robot expression: Neutral
User expression: Pleasure



T6) Robot expression: Hope
User expression: Surprise



T7) Robot expression: Disgust
User expression: Anger



T8) Robot expression: Fear
User expression: Disgust

Fig. 5-7 Captured images of the robot's eye expressions and the user's facial expressions.

5.2 Summary

Regarding our purposed with the principal aspect according to combining mind, which performs by the aspect of hierarchical CBA and the brain biology inspired method for topology learning network which operate by the Topological adaptive resonance theory. We develop the framework including the hardware and software for the robot system based on the pet behavior-like model. Furthermore, for achieving the natural behavior, the robot is implemented combining the motivation-based action, which mainly performs, by the synthetic neurotransmitter dopamine. Moreover, by applying dopamine, the robot can carry out the system of long-term memory module using the inside state of dopamine remain in the cognitive. Especially, in this research proposes the combination of mind and brain-inspired method, particularly emotional intelligence that can let the robot communicate without the human relationship conflict. That why the robot is crucial to have EI.

The CONBE robot successfully demonstrated the system with a human user. The robot can express the sharing emotion with a human, using its emotional intelligence based on the user's facial expression and affective inside state in face-to-face conditions. The robot's emotions also arise from the robot's motivation stimulated by its inside state (i.e., memory) and outside state (the recognition of objects and facial expressions). The system is implemented with the CBA based on the motivation model, facial expression recognition, the robot's eye expressions and the EI-based expression using TopoART-R.

As the demonstration and the proposed system, the CONBE robot with the emotional intelligence by sharing the emotion from the user could enhance the capability of the human affinity, which is strongly important for personal robot. For our further inspiration, we also expect this system can emerge the affective ability to the creature animal due to recent research from the remote animal control which the research proof the nearly future we can connect and control the animal brain (Feng et al., 2007; Li and Zhang, 2016). Consequently, if we embed this artificial emotion intelligence to the animal in near future the animal might communicate with EQ skill likes human that should make the natural cross-communication creature between animal and human. Finally, the suggestion and discussion is also described in the next chapter since belief on expert one’s ear, we experience with our research and observing from the conference specialist in various area.

Chapter 6

Conclusions

6.1 Conclusions

The implementation of the proposed system is the study of emotion generating system based on the robot inside sate motivation and human expression recognition. That is to develop from the conventional model (Consciousness-Based Architecture model) and the related researches, which takes its inspiration from the attempt to give the Conscious Behavior (Conbe) robot to have the recognition, synthetic consciousness and motivation combining the on-line brain-inspire method for generating emotion corresponding to the introspective knowledge and some philosophy. The emotion generating system is to create the emotional variant based on the eight emotional dimensions respect the aspect from Plutchik's wheel of emotion. For example, instantly the robot feels pleasure however in the same time the robot also has other emotions occur at the same time but it is low depend on the meaning of objects or memory. In addition, when the robot can recognize the human expression, the emotional generation is also decide suitable behavior and emotion based on human expression and instant robot emotion to express and empathy that is the main proposed to build up the robot emotion joining human expression. Thus, the emotion generating system is necessary to implement with the artificial neural network for learning the expression decision from robot emotion and human expression. The development concept of our proposed system involves in creating various emotion and expressions using hierarchical ART topology learning with regression function (TopoART-R) for the robots. The emotional system operate with the information from neurotransmitters dopamine, motivation, perception information from the animal vision system and human expression. We thus develop the framework of the emotional and behavior expression to take to the first step of the robot that can expression its emotion and sharing user emotion rather than the convention work that robot usually play with the object surrounding it.

This thesis focuses on three points in the development of our proposed framework: (1) the organization of the behavior including inside-state emotion regarding the phylogenetic consciousness-based architecture which is the eight dimensional model of emotion based on basic emotions; (2) a method whereby the robot can have empathy toward its emotion and human's expressions of emotion to create the robot emotion joining user's expression; and (3) a method that enables the robot to select a facial expression in response to the human user, providing instant human-like 'emotion' and based on sharing emotion with user that uses a biologically inspired topological online method with TopoART-R for generating emotion and expression.

In light of the successful demonstration of our proposed system, we conclude that the CONBE robot with emotional intelligence was able to 'share' emotional expression with the human user. This level of emotional intimacy could be used to enhance robots' capacity for interacting with humans, which is strongly desired in personal robots rather that the robot playing with object and create the emotion that map to the object. However, the robot can express the emotion not only depending on the object but also depending on human expression. The robot's learning system was also improved by the use of the TopoART-R, with which the robot was able to engage in autonomous learning for new patterns of emotion and behavior. We propose a system based on the human-robot interaction application as demonstrated by the results of our present study, including pet-like behavior by the robot using CBA and emotion expression intelligence in face-to-face conditions between the robot and user.

6.2 Recommendations for future research

The present approach is able to be further extended to improve the overall performance of the proposed system, some recommendations for future research are suggested to increase the ability of the robotic system by applying artificial intelligence for memorizing the situation and developing a robot capable to think, learn and take on tasks it hasn't tried before. That would be better to study and investigate other neurotransmitters, such as noradrenaline and serotonin, to combine with the dopamine system for generating a dynamic emotional expression model that is similar to Lövheim cube of emotional model as shown in Fig. 6-1 (Lövheim, 2012). In addition, we hope to improve the FER system to be an independent person FER to ensure that the robot can cooperate with humans in the real world. The accuracy of the facial expression recognition must be high for this purpose. We would also like to combine the system with the online learning algorithm for the behavior and robot emotion expression system to improve the robot's performance in naturally existing with human expression situations.

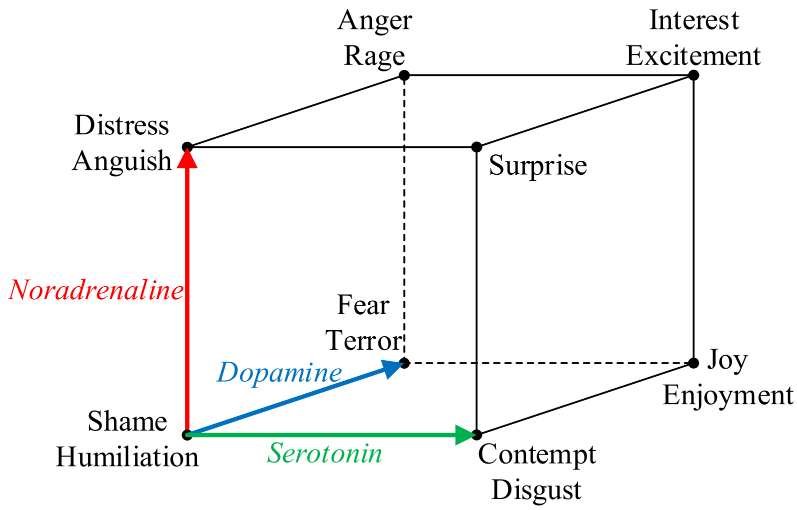


Fig. 6-1 Lövheim cube of emotional model

In light of recent research into remote animal control (Talwar et al., 2002), we speculate that our new system could be adapted to connect with and control an animal's brain, merging the affective ability of the robot with the animal. Consequently, if we embed this artificial social-emotional intelligence into an animal, the animal might be able to communicate with emotional intelligence-based skills similar to those of humans, which could make natural cross-communication between animals and humans possible.

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Appendix

A. Publications and Presentations from the Present Research Work

Journal

1. Sakmongkon Chumkamon, Eiji Hayashi and Koike Masato, “Intelligent Emotion and Behavior Based on Topological Consciousness and Adaptive Resonance Theory in a Companion Robot,” Biologically Inspired Cognitive Architectures (BICA), Vol.18, October 2016.
2. Sakmongkon Chumkamon and Eiji Hayashi. “Recognized Face Tracking for CONBE Robot,” in Journal of Robotics, Networking and Artificial Life, pp 140-144, September 2014.

Conference

1. Sakmongkon Chumkamon and Eiji Hayashi, “Social Expression of Pet Robot Based on Artificial Consciousness and Biologically Inspired Online Topological Method,” in The 2016 International Conference on Artificial Life and Robotics (ICAROB 2016), January 29-31, 2016
2. Sakmongkon Chumkamon, Koike Masato, and Eiji Hayashi, “Facial Expression of Social Interaction Based on Emotional Motivation of Animal Robot,” In Systems, Man, and Cybernetics (SMC), 2015 IEEE International Conference on, pp. 185-190. October 9–12, 2015.
3. Sakmongkon Chumkamon, and Eiji Hayashi, “ConBe robot: The development of self-perception and expression in face-to-face interaction,” In Soft Computing and Intelligent Systems (SCIS), 2014 Joint 7th International Conference on and Advanced Intelligent Systems (ISIS), 15th International Symposium on, pp. 769-775, December 3 – 6, 2014.
4. Sakmongkon Chumkamon, Koike Masato, and Eiji Hayashi, “The robot's eye expression for imitating human facial expression,” in Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), 2014 11th International Conference on, pp. 1-5, May 14-17, 2014.
5. Sakmongkon Chumkamon, and Eiji Hayashi, “Facial expression recognition using constrained local models and Hidden Markov models with consciousness-based architecture,” in System Integration (SII), 2013 IEEE/SICE International Symposium on, pp. 382-387, December 15 – 17, 2013

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