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Cognitive Robotic Engine: Behavioral Perception Architecture for Human-Robot Interaction

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1. Introduction

For personal or domestic service robots to be successful in the market, it is essential for them to have the capability of natural and dependable interaction with human. However, such a natural and dependable human-robot interaction (HRI) is not so easy to accomplish, as it involves a high level of robotic intelligence for recognizing and understanding human speech, facial expression, gesture, behavior, and intention as well as for generating a proper response to human with artificial synthesis. It is our view that the first key step toward a successful deployment of HRI is to level up the dependability of a robot for recognizing the intention of the human counterpart. For instance, to date, robotic recognition of human speech, as well as human gestures, facial expressions, let alone human intention, is still quite unreliable in a natural setting, despite the tremendous effort by researchers to perfect the machine perception individually for recognizing the aforementioned human expressions and intentions. We observe that the robustness and dependability human enjoys in human-human interaction may not merely come from the fact that human has powerful perceptual organs such as eyes and ears but human is capable of executing a series of behaviors associated with a perceptual goal, for instance, the behaviors related to the collection of additional evidences till the decision is sufficiently credible. In analogy, we claim here that the dependability of robotic recognition of human intention for HRI may not come from the perfection of the individual capabilities for recognizing speech, gesture, facial expression, etc. But, it comes with the automatic generation of robotic behaviors that makes sure reaching a credible decision for the given perceptual task.

We present here “Cognitive Robotic Engine (CRE)” that automatically generates perceptual behaviors for selecting and collecting an optimal set of evidences, leading to a dependable and robust recognition of human intention under a high level of uncertainty and ambiguity. Note that the dependability of robotic perception may not come from "the perfection of individual components for perception," but from "the integration of individual components into dependable system behaviors, no matter how imperfect and uncertain individual components may be." CRE presents a novel robotic architecture featuring 1) the spontaneous establishment of ad-hoc missions in connection to perceptual goals, 2) the determination of an optimal set of evidences to be selected and/or collected for processing based on in-situ monitoring of the current situation, 3) the integration of such behavioral building blocks as mission management, evidence selection, evidence collection, evidence fusion and filtering for decision-making in an asynchronous and concurrent architecture, and 4) the implementation of behavioral personality of a robot under CRE framework. We applied CRE to a robot identifying a caller in a crowed and noisy environment. The experimental results demonstrate the great enhancement of the dependability of robotic caller identification through the proposed behavioral perception approach to HRI based on CRE.

1.1. Issues involved in Conventional approach to Human-Robot Interaction

One of the key reasons that the robot market does not evolve yet, despite various prototype service robots show very impressive performance in recent years is that, unlike human-human communication, it is difficult to interact with the robot using language, gesture, facial expression, etc. Accordingly, development of a robot interacting with people more naturally is a very important issue to robot researchers for popularization of robotics (Font T, et al., 2003). So many researchers have been developing the technology for understanding human expression such as speech recognition, gesture recognition, understanding human facial expression and so on. And their recent research results show excellent recognition capabilities in their individual field (Sakaue, et al., 2006, Betkowska, et al., 2007).

However, according to circumstances, development of individual modules such as face recognition and speech recognition module does not guarantee an increment of robot reliability enough to interact with human naturally. For example, in real dynamic environments, a hard situation for human face recognition like a dark room has lead to occasional recognition problems. Similarly it would be difficult for a robot to understand human speech in the noisy environment. And although dependability of individual modules is improved, there show unreliable results sometimes. Therefore, there is a certainly need of research on integrating each component module, method of proper module selection from the existing state of things for natural human-robot interaction (HRI).

The "Cogniron" Project of the European Union (EU) has studied advancement of component and multi-modal approaches in order to make more friendly robot (Fritsh, et al., 2005 and Li, et al., 2005, 2007). A multi-modal interaction framework deals with the fusion of multiple human-robot interaction modules to reduce dependence on the single specified sensor data. However it does not address the robot behavior for more active collection of evidences. Some research has been done on the topic of a reduction of the process uncertainty using audio-visual integration (Choi, et al., 2006). In order to find speaker localization, they use probabilistic method based on bayesian theorem, but they do not deal with process of automatic evidences selection (herein evidences mean features such as human face, skin, calling voice, gesture, etc.). The paper on a robot photographer is also very interesting (Ahn, et al., 2006). A photographer robot is able to find the person who wants to have taken pictures using two processes that face detection and gesture detection. But if the caller suddenly disappears the robot might be not able to find the caller because this robot does not have the active evidence collection behaviors. Chen Bin and Kaneko Masahide proposed the robot behavior selection method based on integration of multimodal information (Bin & Masahide, 2007). This paper mentions robot behaviors; however these behaviors are not active action for a reduction of mission uncertainty. In order words, the robot does not take an action for evidence collection such as searching, wandering and approaching.

As previously stated, despite the rise of the requirements on service robots which can interact with people naturally, few have attempted to address increment of robot reliability from a synthetic point of view. Therefore, in this paper we proposed "Cognitive Robotic Engine (CRE)" leading to a dependable and robust recognition of human intention in the dynamic real environments.

2. Cognitive Robotic Engine (CRE): Conceptual Overview

Before introducing the concept of CRE, let us consider how a human recognizes objects/people in the uncertain environment, e.g., a dark room, crowded and noisy party, etc. It is not easy for a robot to identify objects/people in such places. Because some objects seem very similar in a dark place and he or she is hard of hearing in noisy place. However, a human is able to identify them. In this situation, how is a human able to recognize them? What would he or she take action to recognize something/someone? Though human decision making shows different aspects sometimes under uncertain situation (Neves & Raufaste, 2001), in most cases, people make the decision or take some action for reducing the uncertainty through the following procedure when finding some objects/people. If he or she heard his/her name from behind, but he or she was not confident because that place is so loud, he/she looked back in order to find who's calling. If someone is supposed to find a specific object in a dark room, but if there are several similar objects, he or she must approach the object, and then take some proper action such as touch to recognize the object. In order words, a human takes appropriate actions for gathering more information (Wilson, 2000). In addition, a human makes a decision using not a specific sense but all the information.

The concept of CRE like this, that is, CRE integrates information to accomplish dependable perception and recommends appropriate actions for gathering more information. It is regarded as a more general form of behavior based approach that is extended to include perceptual behavior (Arkin, 1998). Imitating the human dependability in perception, the main features and procedures of CRE is conjectured as follows:

1) The spontaneous and self-establishment of ad-hoc perceptual missions in connection to particular sensing.

2) The choice of particular asynchronous and concurrent flow architecture of perceptual building blocks, out of a potentially huge number of possible flow architectures as the basis for deriving evidences to be fused together.

3) The incorporation of action blocks into the chosen asynchronous and concurrent flow architecture of perceptual building blocks as a means of proactively collecting sensing data of less uncertainty and of new evidence, which triggers a dynamic reorganization of the asynchronous and concurrent flow architecture of perceptual building blocks.

4) The optimal process control in terms of the choice of a particular asynchronous and concurrent flow architecture of perceptual building blocks to follow as well as of the choice of particular action blocks to be invoked at each sampling time, where the optimality is defined in terms of the time and computing resources for uncertainty reduction. Note that the control strategy may differ by individuals.

3. CRE Architecture

Overall architecture of CRE system is shown in Fig. 1. CRE consists of three parts, perceptual part, control part and action part widely. Perceptual part is composed of sensors, perceptual processes which are processed asynchronously and concurrently, precedence and evidence fusion relations through which a robot perceives the environment like a human. Control part takes charge of invoke mission or mission transition and it controls behavior selection or behavior changing. Finally, action part is in charge of robot action such as searching, approaching, and gazing. The system operating procedures are as follows: 1) the sensors receive and transmit external data, 2) the perceptual processes analyze the information, 3) the control part gathers all the information from perceptual processes, and then make a decision, 4) if there is any necessity the action part makes the robot to act. Note that system operates asynchronously.

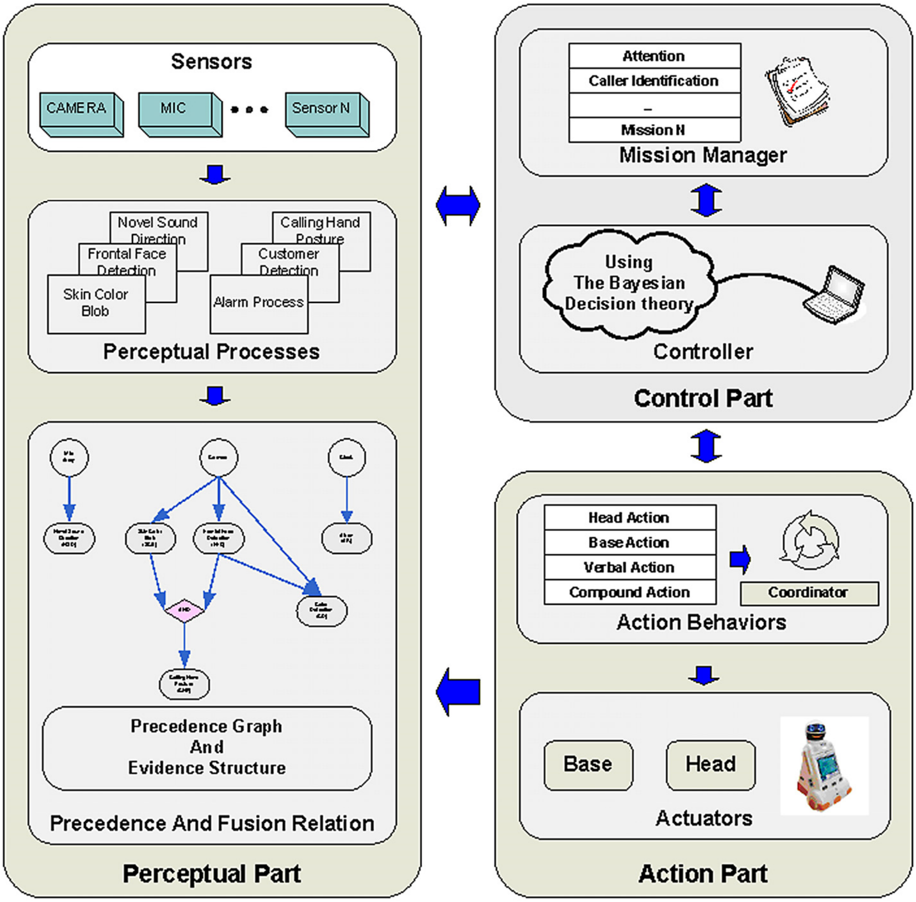

Figure 1. Overall Architecture of Cognitive Robotic Engine

3.1 Perceptual Process and Precedence Relation

The perception process of CRE means basic building block for the entire perception. Table I represents the specification of all perceptual processes – Novel Sound Detection (NSD), Frontal Face Detection (FFD), Skin Color Blob (SCB), Calling Hand Posture (CHP), Color

Detection (CD), and Alarm (AL). Normally, the output of individual perceptual process has calculated certainty (CF), spatial probability distribution (SP), action candidates that can improve the certainty factor (AC), processing time (PT), and packet recording time (RT).

NSD	Def.	When the sound volume exceeds the threshold, estimates the direction of source
	Source	Mic array (3 channel)
	Input	Raw data of sound
	Output	Direction of novel sound Calculated Certainty (CF) Spatial probability distribution (SP) Candidate of Action (AC) Processing Time (PT) Packet recording Time (RT)
FFD	Def.	Finds face region by image feature
	Source	Camera
	Input	Raw image from Camera
	Output	Coordinate, and size of detected face CF, SP, AC, PT, RT
SCB	Def.	Distinguishes skin region by RGB condition and makes others black in image
	Source	Camera
	Input	Raw image from Camera
	Output	Image of skin color segmentation Most probable direction that callers exist in. CF, SP, AC, PT, RT
CHP	Def.	Estimates calling hand by skin color in face adjacent area
	Source	FFD, SCB
	Input	Coordinate and size of detected face Skin segmented image
	Output	Direction, and distance of caller CF, SP, AC, PT, RT
CD	Def.	Estimates clothing color of a person who is detected by FFD process.
	Source	Camera, FFD
	Input	Coordinate and size of detected face
	Output	Estimated clothing color (Red/Blue) CF, SP, AC, PT, RT
AL	Def.	Send alarm signal at reservation time
	Source	Time check Thread
	Input	Current time
	Output	Alarm signal Information of reserved user CF, SP, AC, PT, RT

Table 1. Description of Perceptual Processes

If the outputs of one or more processes are necessary as an input or inputs of another for processing, a relationship between the processes defines precedence relation. Each process is assumed independent as long as they are not under precedence restrictions. Fig. 2 shows the precedence relation of all perceptual processes of system.

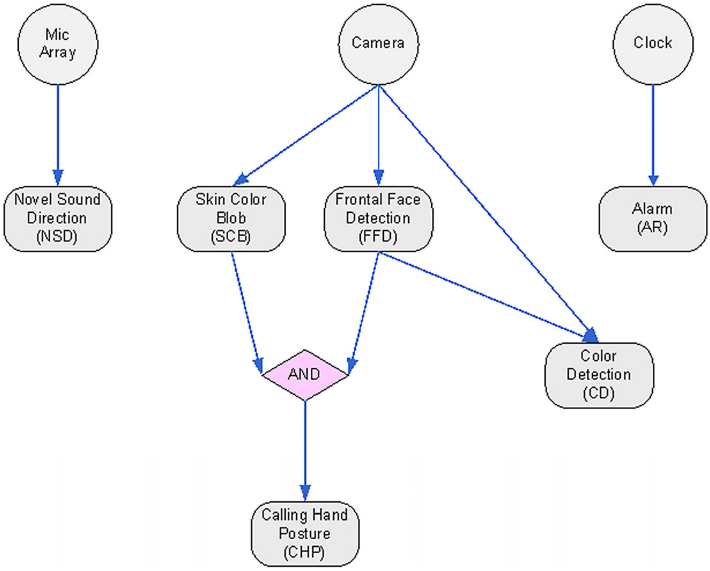

Figure 2. The precedence relation of all perceptual processes – All the relations without AND mean OR

4. In-Situ Selection of an optimal set of evidences

4.1 Evidence Structure for the Robot Missions

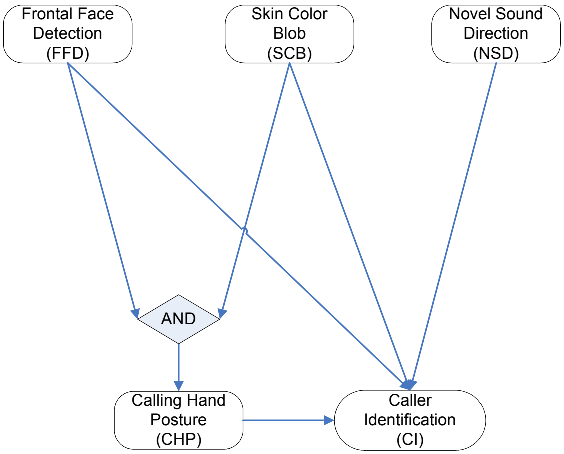

Figure 3. Evidence Structure For Caller Identification Mission

CRE aims at combining or fusing multiple evidences in time for dependable decision. In order to integrate multiple evidences, we needed another relation graph for certainty estimation. Although, above mentioned precedence relation graph shows the input-output relation of each perceptual process nicely, however it is not suitable for certainty estimation. Because to calculate certainty of the mission, the robot applies difference shape of calculate expression to each mission. Therefore, we define the "evidence structure" for certainty estimation.

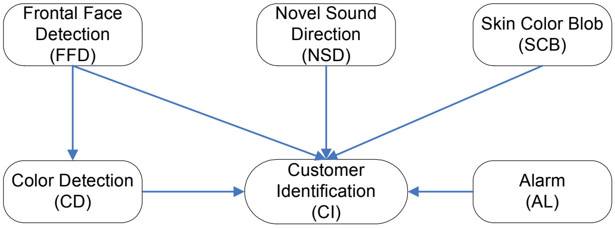

Figure 4. Evidence Structure For Customer Identification Mission

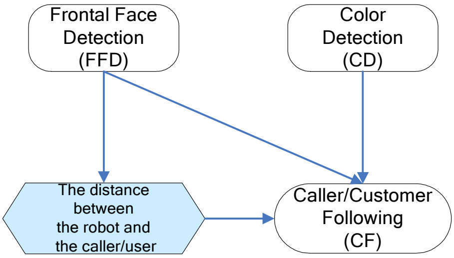

Figure 5. Evidence Structure For Caller/Customer Following Mission

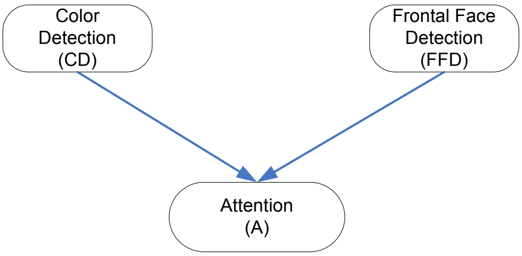

Figure 6. Evidence Structure For Attention Mission

Our analysis of current service robot's ability tell us that main objects of service robot are recognizing user and providing information to the user. Therefore, bring a current service robot platform into focus, we created four missions which are caller identification, customer identification, caller/customer following and attention. Consequently, evidence structure was made suitability for each individual mission. The robot selects adapted evidences for using this structure. The reason why we was not make one united structure but made individual structures for four missions is that if some missions are extended in the future, it is difficult to design architecture graph to extended missions. The evidence structure described by Fig. 3 through Fig. 6 is equivalent to a Bayesian net, except that we consider explicitly the conjunctions of evidences that becomes sufficient for proving the truth of another evidence and represent them with AND operations. This is to make it easier to define the joint conditional probabilities required for the computation of certainties based on the Bayesian probability theorem. The actual implementation of computing certainty update is based on the Bayesian net update procedure.

4.2 Certainty Estimation based on Bayesian Theorem

In this paper, we calculate the mission certainty based on Bayesian theorem.

$$
\begin{aligned}
& Mission\,Certainty\,(Mission) = \\
& P(Mission \mid Evidences) = \frac{1}{1 + \dfrac{P(Evidences \mid \overline{Mission})P(\overline{Mission})}{P(Evidences \mid Mission)P(Mission)}} = \frac{1}{1+\alpha} \\
& \therefore\ \alpha = \frac{P(Evidences \mid \overline{Mission})P(\overline{Mission})}{P(Evidences \mid Mission)P(Mission)}
\end{aligned}
\tag{1}
$$

(1) shows that the formula of the mission certainty estimation. In here, α is calculated differently in each mission. Under assumption that each evidence is independent, from the evidence structures, we are able to calculate α. For example, if the caller identification mission is selected, α is calculated by formula (2).

$$
\alpha = \frac{p(FFD \mid \overline{CI})p(SCB \mid \overline{CI})p(NSD \mid \overline{CI})p(CHP \mid \overline{CI})p(\overline{CI})}{p(FFD \mid CI)p(SCB \mid CI)p(NSD \mid CI)p(CHP \mid CI)p(CI)} \tag{2}
$$

The rest α value of individual missions as follows:

- Customer identification

$$
\alpha = \frac{p(FFD \mid \overline{CI})p(SCB \mid \overline{CI})p(NSD \mid \overline{CI})p(CD \mid \overline{CI})p(AL \mid \overline{CI})p(\overline{CI})}{p(FFD \mid CI)p(SCB \mid CI)p(NSD \mid CI)p(CD \mid CI)p(AL \mid \overline{CI})p(CI)} \tag{3}
$$

- Caller/Customer Following

$$
\alpha = \frac{p(FFD \mid \overline{CF})p(CD \mid \overline{CF})p(\overline{CF})}{p(FFD \mid CF)P(CD \mid CF)p(CF)} \tag{4}
$$

- Attention

$$
\alpha = \frac{p(CD \mid \overline{A})p(FFD \mid \overline{A})p(\overline{A})}{p(CD \mid A)p(FFD \mid A)p(A)} \tag{5}
$$

4.3 Certainty Estimation with Consider Space-Time

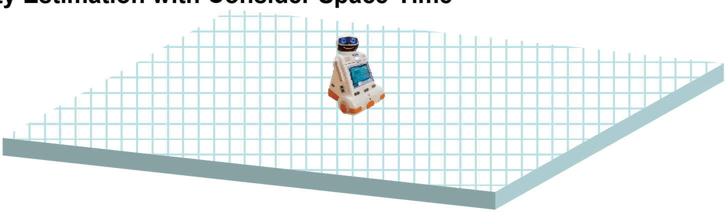

Figure 7. Interaction Space of the Robot for Certainty Representation

In this research, we implemented all perceptual processes with considering the two-dimensional interaction space of the robot. Fig 7 shows that interaction space of the robot. The interaction space is represented by 81(9*9) cells and each cell has around 50cm*50cm size. Since all processes have the information of two-dimensional space, each mission certainty is also represented by two-dimensional space and it is calculated for each cell. Therefore, the robot has spatial information. The spatial probability distribution is changed according to the robot behaviors and is estimated according to evidences continually.
Moreover, in order to provide time-related service, we implemented alarm process (AL). Using this process, the robot is able to provide service such as delivery information for the customer at specific time.

5. Evidence Collection Behaviors

The action should be selected to eliminate uncertainty of mission, not uncertainty of individual process. This means that the selected action has to improve the mission certainty best. Let B = {b1,b2, … , bn} is a set of proposed actions by a set of perceptual processes P= {p1, p2, … pn}, at time t. From the perceptual process, we can estimate the variation of certainty when the robot takes an action below.

b1 → ΔC(b1) = {Δc1(b1), Δc2(b1), … , Δck(b1), … ,Δcn(b1)}
b2 → ΔC(b2) = {Δc1(b2), Δc2(b2), … , Δck(b2), … ,Δ cn(b2)}
…
bk → ΔC(bk) = {Δc1(bk), Δ c2(bk), … ,Δck(bk), … , Δ cn(bk)}
…
bn → ΔC(bn) = {Δc1(bn),Δ c2(bn), … , Δck(bn), … , Δcn(bn)}

where Δck(bk) is expected certainty variation of pk when the action is selected. ΔC(bk) is a set of variation values. Now we can select an action using (6).

$$\begin{aligned}&Selection\ of\ action =\\&b_{\max}\{P(callerID \mid Evidences + \Delta C_{b1}),\ldots,P(callerID \mid Evidences + \Delta C_{bn})\}\end{aligned} \tag{6}$$

The selected action will increase the mission certainty best.

6. Mission Management

Most of developed service robots recognize their mission by user's manual input. However, to provide advanced service, if there are several missions, the robot should be select mission naturally. Accordingly, we implemented the mission manager for advanced service of a robot. The mission manager should tell the mission with the minimum of perceptual processes.
The roles of mission manager are detailed below:

1. The manager should be monitoring enabled perceptual processes.
2. If any change of environment stimulus some perceptual process, the manager has to recognizes all the missions which are related to the process. The connection relation between missions and perceptual processes should be pre-defined.

3. Since enabled perceptual processes are very primitive, some missions will remain and be invoked among the subset of missions, or the others may be removed. To recognize which of them to be selected, additional perceptual processes should be enabled.
4. If there is one mission selected, the manager performs it, while the number of mission is bigger than one, they are took into queue based on the priority of missions. Note that, simultaneous and multiple mission will be considered later.
5. Performing a mission, the manager should check if the mission is on going, or success, or fail
6. With succeed/failure of the mission, the manager should change the state of robot naturally.

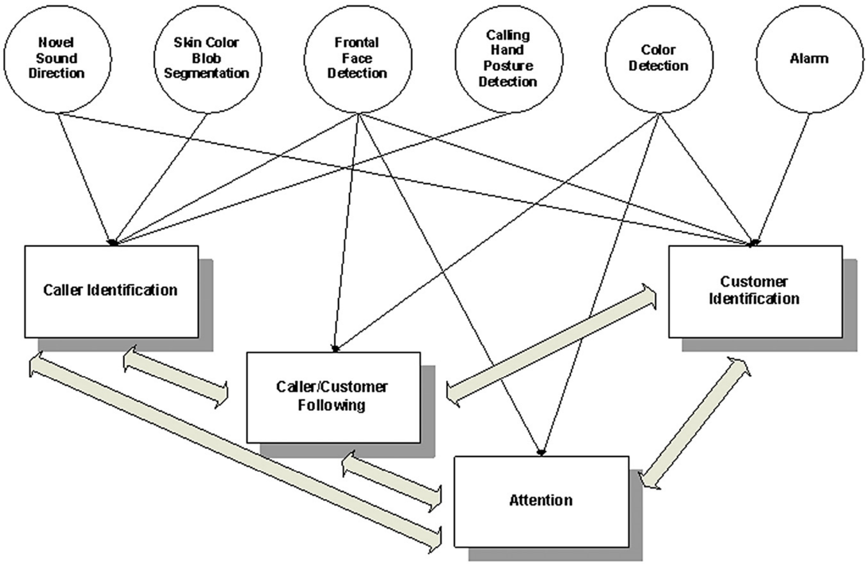

Figure 8. Mission Manager for Four Missions

Mission	Definition
Attention	Gazes into Caller/Customer
Caller Identification	Seeks for the caller and then identifies the caller
Customer Identification	Seeks for the customer and then identifies the customer
Caller/Customer Following	Follows the caller/customer

Table 2. List of missions and definition

7. Implementation

7.1 Hardware Specification

The approach outlined above has been implemented on the mobile robot iRobi. The specification of single-board-computer has Intel Pentium mobile processor 1.40GHz, 1GB

RAM. And the Robot has three channel microphones for estimates the direction of sound source. Logitech Quickcam Pro 3000 camera as imaging sensor has approximately 60° horizontal-field-of-view (HFOV) and 320*240 square pixels.

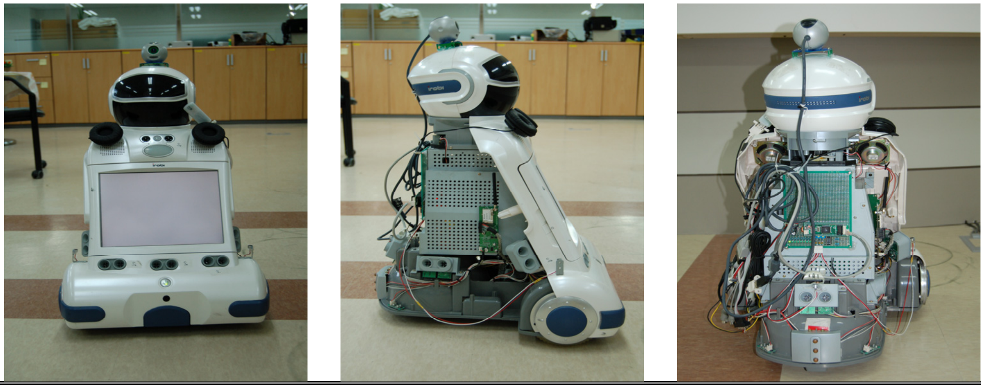

Figure 9. Robot Hardware

7.2 Software Configuration

Overall architecture of the CRE system is presented in Fig. 10. As seen in the figure, the system is composed of server and client. In here, client means the robot and the robot and the server communicated by Common Robot Interface Framework (CRIF). It provides TCP/IP wireless connection so that CRE system could be adapted to another platform easily. Two multi threads in the server request image and sound continuously. A perceptual process is called when a thread get sensing information from robot. There procedures are operated asynchronously and concurrently.

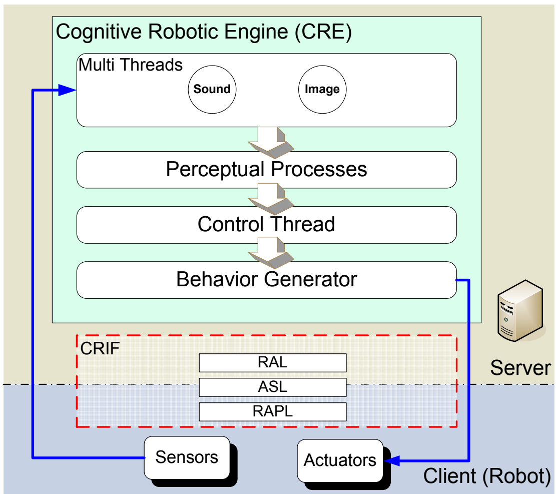

Figure 10. Overall Architecture of the System. (RAL: Robot API Layer, ASL: API Sync Layer, RAPL: Robot API Presentation Layer)

7.2.1 Sampling Time of Control based on Forgetting Curve

Among the several approaches for sampling time, we got the idea from psychology field (Brown, 1958, R. Peterson & J. Peterson, 1959, Atkison & Shiffrin 1968). Fig. 11 shows forgetting curve for human short-term memory. Based on that, the sampling time is determined as 600ms approximately.

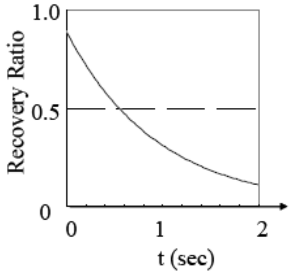

Figure 11. Forgetting curve of Brown Peterson paradigm

8. Experimentation

8.1 Experiment Condition

The experimental scenario is described in Fig. 12. Experimentation had proceeded in the around 6m*8m size tester bed without any obstacles and the caller is only one. Please see the figure with attention time and variance of the mission. Descriptions on abbreviation as below: NSD: Novel Sound Detection, FFD: Frontal Face Detection, SCB: Skin Color Blob, CHP: Calling Hand Posture , CD: Color Detection, AL: Alarm.

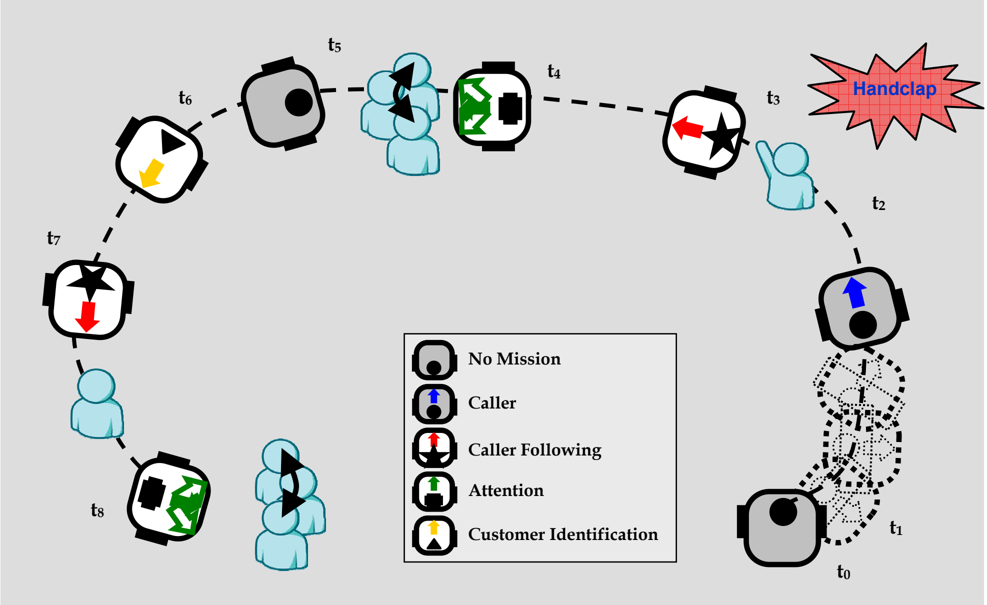

Figure 12. Experimentation of the multi-mission management and the certainty estimation of Cognitive Robotic Engine

8.2 Experiment Results

Initially, control part of CRE enables only NSD , FFD, AL processes.
First (t0), the caller called the robot behind the robot's back through the handclap. Then, the certainty of caller identification mission arisen as Fig. 13 by NSD process output, and the mission started (t1).

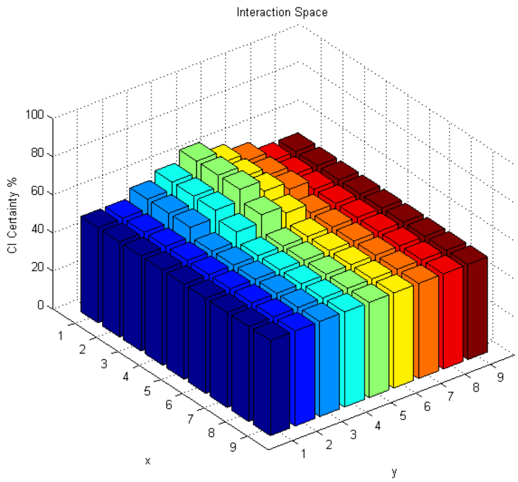

Figure 13. Certainty of the caller identification mission (t1)

As the caller identification mission started, SCB and CHP processes activated to collect more evidences. Fig. 14 is certainty of the mission, just after turning to the caller, and the certainty increased when FFD and CHP processes detected caller's hand motion (Fig. 15).

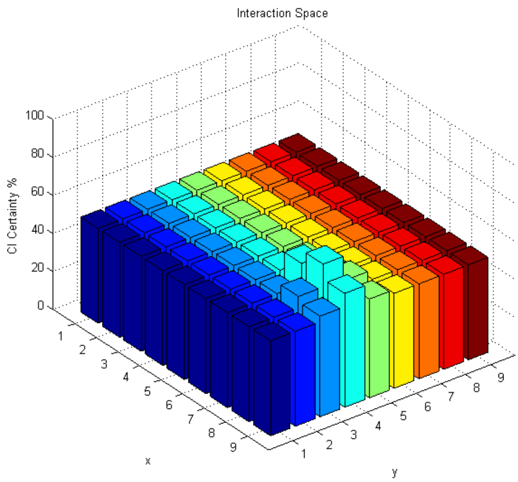

Figure 14. Certainty of the caller identification mission (t2, before calling hand posture detected)

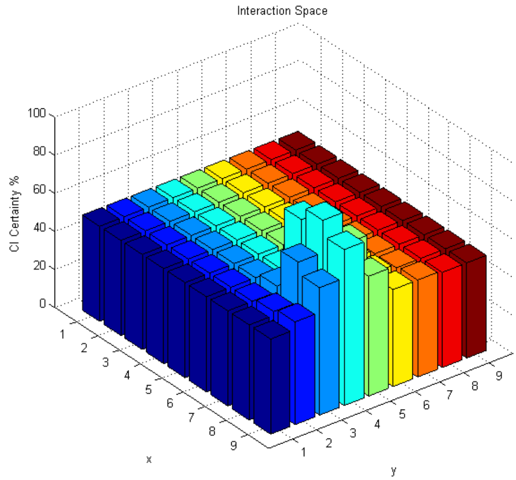

Figure 15. Certainty of the caller identification mission (t2, after calling hand posture detected))

At this moment (t2), the mission manager changed the mission to caller tracking. So, FD and CD processes activated, and started to move to the caller (t3). Fig. 16 shows the certainty of caller tracking mission at t3. In Fig. 17, the certainty of frontal spaces of the robot is high enough to change the mission to attention (t4).

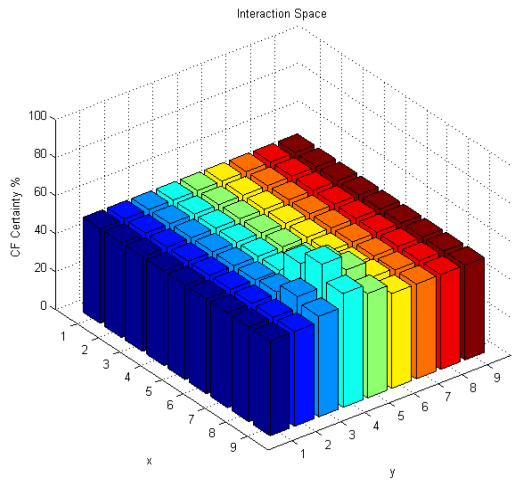

Figure 16. Certainty of the caller/customer tracking mission (t3)

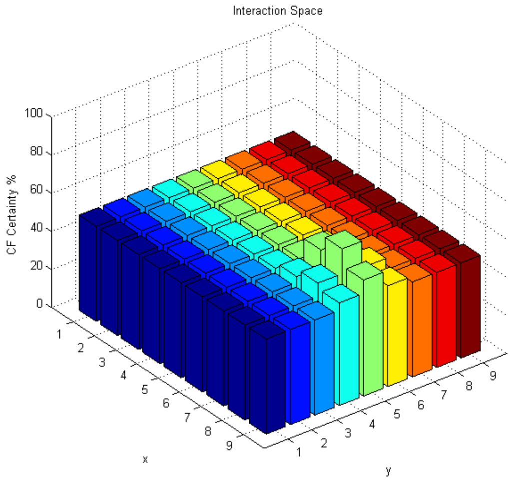

Figure 17. Certainty of the caller/customer tracking mission (t4)

Fig. 18 shows the certainty of attention mission. Generally, the service robot can convey information to the caller while doing attention mission. After a communication with the caller, mission manager of the robot dismissed attention mission like initial state. After for a while, the customer identification mission started by AL process, so the robot try to find customer who wears red shirt (reserved mission like timer). The certainty of customer identification mission is shown Fig.19 (t4). When the robot found the customer, the certainty changed like Fig. 20, then, attention mission started (t8).

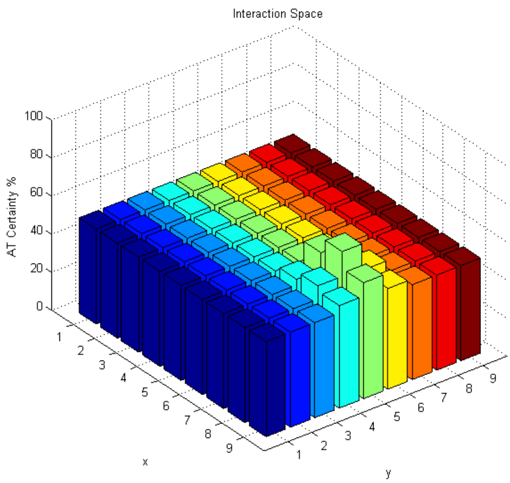

Figure 18. Certainty of the attention mission (t4)

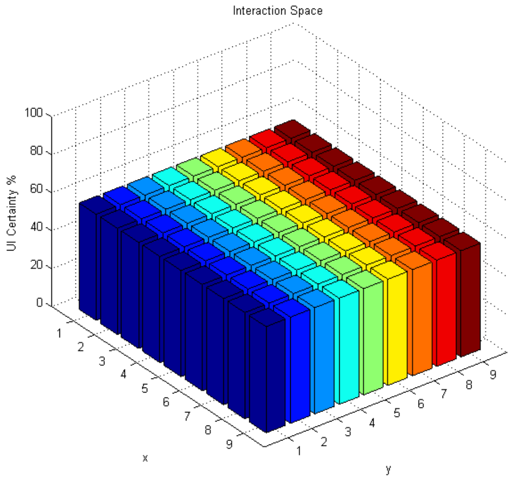

Figure 19. Certainty of the customer identification mission (t6)

We recorded the results several times of experimentation, the results shows that missions started, stopped and changed automatically based on variation of the certainty, and by defining the certainty of each mission in the interaction space, behavioral parameters can be easily obtained. Basic rules to choose behavior is that select one behavior among candidates suggested by perception processes to increase their certainties.

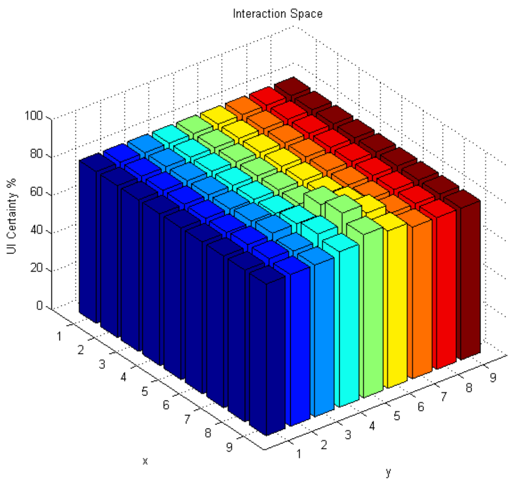

Figure 20. Certainty of the customer identification mission (t7)

9. Conclusion and Future work

In this paper, we described the robotic architecture for dependable perception and action for service robot in dynamic environment. This architecture is organized to accomplish perception mission in spite of the integration of imperfect perception processes, and updated for managing multi-missions. The next step, we are planning to research on automatic discrimination method of system dependability.

10. Acknowledgement

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