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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. 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 of reaching a credible decision for the given perceptual goal.

We present here "Cognitive Robotic Engine (CRE)" that automatically generates such perceptual behaviors as selecting and collecting an optimal set of evidences, for dependable and robust recognition of human intention under a high level of uncertainty and ambiguity. CRE is to demonstrate 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 Approaches to Human-Robot Interaction

A natural HRI has been an interesting subject of research in robotic community for sometime as a means of establishing viable robotic service to human (Font T, et al., 2003). Accordingly, there have been developed various technologies for understanding human expressions such as speech recognition, gesture recognition, understanding human facial expression, etc. Many of the recent research results show significant advancement in their recognition capabilities for individual sake (Sakaue, et al., 2006, Betkowska, et al., 2007).

However, the advancement of individual components such as face and speech recognition themselves does not guarantee the dependability of HRI required for natural human robot interaction. For instance, recognition of human face or speech becomes problematic should robot be in dark, noisy, or dynamic environment. And, it is a growing consensus that efforts to perfect such individual components may be neither fruitful nor justified. Instead, it makes more sense to integrate individual components into a meaningful cognitive process or behavior that guarantees the required dependability.

In an attempt to generate a more user friendly robot, the EU "Cogniron" Project has adopted the multi-modal interaction framework where multiple human-robot interaction components are fused in order to reduce the dependence of the decision on, potentially uncertain, individual components. (Fritsh, et al., 2005 and Li, et al., 2005, 2007). Similarly, the integration of audio-visual cues based on Bayesian theorem has been conducted in order to deal with uncertainties in speaker localization (Choi, et al., 2006). For the development of a robot photographer, face and gesture detection components are integrated to identify the caller among a crowd of people (Ahn, et al., 2006). However, these approaches stop at the level of reducing uncertainties instead of reaching the level of a cognitive process for dependability in which robot self defines its own missions and generates behaviors for automatically selecting and collecting evidences. It may be interesting to note the work of Bin & Masahide where behavioral status is used to determine visual attention as a cognitive process for automatically selecting optimal evidences (Bin & Masahide, 2007).

Cognitive Robotic Engine (CRE) presented in this chapter aims at establishing a biologically inspired cognitive process that provides dependable and robust recognition of human intention in real noisy environments.

2. Cognitive Robotic Engine (CRE): Conceptual Overview

As an introduction of the concept of CRE, let us consider how a human identifies a caller, if there is, dependably despite the adverse condition of, say, a crowded and noisy party environment. Upon hearing a novel but highly uncertain nature of sound that may indicate someone calling, one immediately registers in his/her consciousness an ad-hoc mission of verifying if there is a caller, if any. This ad-hoc mission will remain in his/her consciousness till the verification is done with a sufficient level of confidence an individual set. With the

registered mission producing a stress, a flurry of asynchronous and concurrent perceptual processing takes place inside in such a way as to reduce the uncertainty as efficiently as possible.

The asynchronous and concurrent perceptual processing starts with laying out an asynchronous and concurrent flow of perceptual building blocks spontaneously, from which a sufficient amount of evidences are collected for the registered ad-hoc mission. The basic perceptual building blocks represent the perception units of various levels of abstraction and complexity, ranging from a lower level of elementary sensing primitives to a higher level of conceptual recognition units. These building blocks are assumed predefined, although individuals may have a different number, type, and quality of these building blocks. In the above example, a sufficient amount of evidences may be quickly assembled from multi-modal sensing cues, including both auditory and visual cues such as calling hand gestures and/or calling facial expressions, generated by an asynchronous and concurrent flow of auditory and visual perception building blocks. Potentially, there may exist a large number of possibilities for laying out an asynchronous and concurrent flow of building blocks, with individual sensors as origins, and for acquiring distinct evidences from different paths of the chosen asynchronous concurrent flow. However, to explore all the possible flows of evidences may be neither possible due to a limit in computational resources, nor desirable for efficiency in time and energy. The key may be to understand an optimal way of constructing an asynchronous concurrent flow of perceptual building blocks for decision, dynamically to the real-time variation of situations and, perhaps, similarly to the way our brain functions.

An asynchronous and concurrent flow of perceptual building blocks is connected to the actions to be taken proactively to collect sensing data of less uncertainty or of additional evidences. Human seldom depends passively on what is sensed only for a decision, if the sensed information is incomplete or uncertain. Rather, human tends to take appropriate actions for gathering a better quality of or a new addition of information. For instance, in the above example, to reduce uncertainty, one may resort to look around to see if he/she can find someone making a calling gesture or to generate a confirmation call, like " is there anybody calling? ", to get a reply. Human dependability of perception is thus deeply linked to the proactive actions for assisting and guiding perception by incorporating action building blocks into an asynchronous and concurrent flow of perceptual building blocks. Action building blocks range from an actuator level of action primitives to a task level of functional units. To explore all the possible ways of incorporating action blocks into a perceptual flow may be prohibitive or infeasible due to a potentially large number of possibilities that action blocks can be incorporated, due to the existence of possible conflicts among action blocks, or due to the cost in time and energy that is associated with taking actions. The key is how to choose action blocks to be incorporated into an asynchronous and concurrent flow of perceptual building blocks in such a way as to achieve an optimal overall efficiency in reaching the decision. This requires evaluating an action block as an information source against the cost in time and energy to exercise it.

Summarizing the above, human dependability in perception may be conjectured as the result of the following exercises:

1.   The spontaneous and self-establishment of ad-hoc perceptual missions in connection to particular sensing that drive the subsequent perceptual processes till satisfied.

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 energy to be consumed for completing the ad-hoc mission, which is in turn a function of the amount of uncertainty reduction and the time and computational resources required for completing the perceptual and action building blocks to be processed. Note the control strategy may differ by individuals since some heuristics are involved in the strategy, due to the complexity of search space leading no definite optimal solution is feasible. However, it is interesting to see that this heuristics actually represent a personality of an individual or a robot that we can exploit for creating robots with personality.

The environment or toolkit that enables the above asynchronous and concurrent flow of a perceptual process, or, in general, a robotic process, is referred to here as Cognitive Robotic Engine (CRE). In what follows, we present a more details on how to implement the above concept in computer by describing 1) an asynchronous and concurrent architecture for CRE with the definition of perceptual and action building blocks, the representation of search space with the partial order and fusion relation of perceptual building blocks as well as with the exclusion relation and organized actions for action building blocks, 2) a method of connecting perceptual and action building blocks, 3) an optimal control of CRE with self-establishment of ad-hoc missions, of choosing a particular flow architecture with the optimality in terms of speed and time, and, finally, 4) a demonstration of the value of CRE by a caller identification experimentation with a robot .

3. CRE Architecture

Overall architecture of CRE system is shown in Fig. 1. CRE consists of three major parts, perceptual, control and action parts. 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.
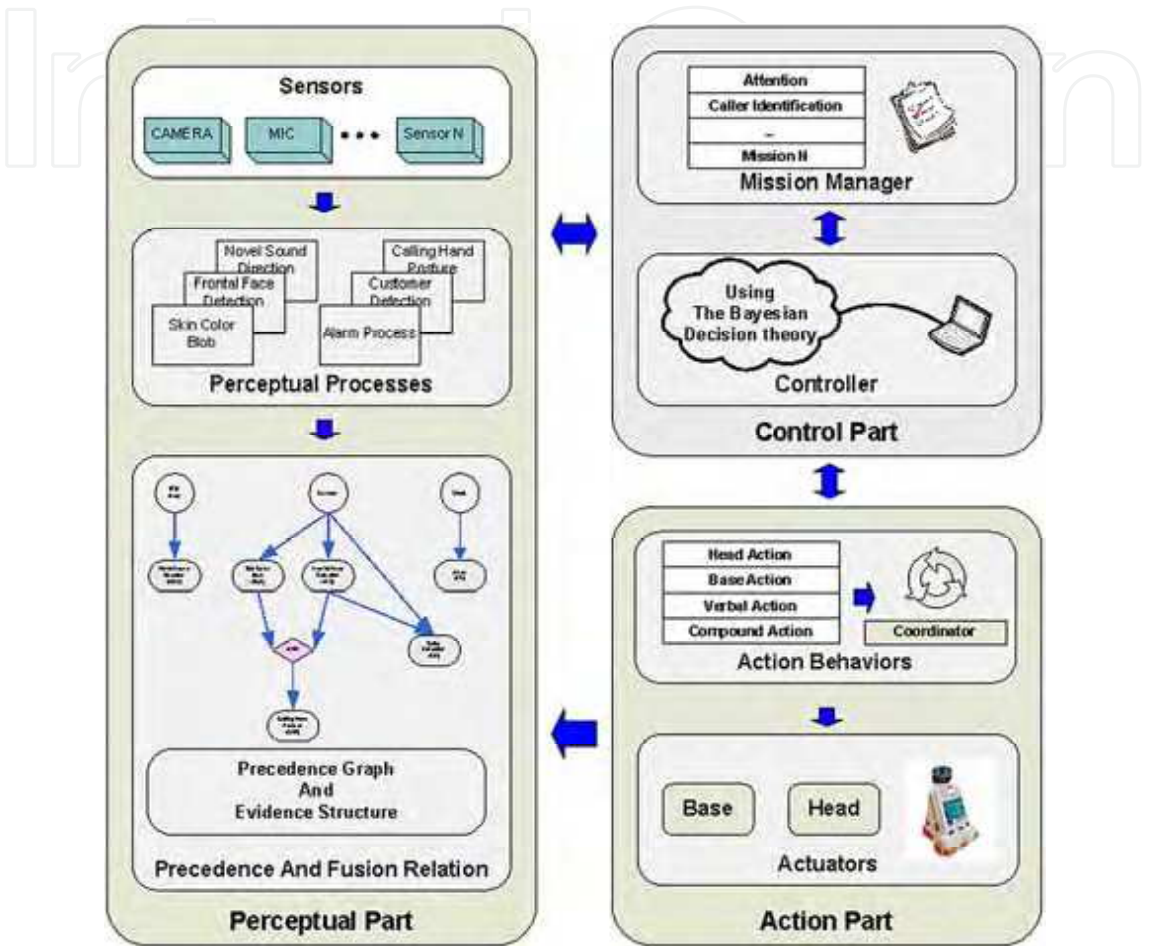
Figure 1. Overall Architecture of Cognitive Robotic Engine

3.1 Perceptual Process and Precedence Relation

Present CRE architecture and all perceptual processes have been organized to accomplish the caller identification mission. 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.
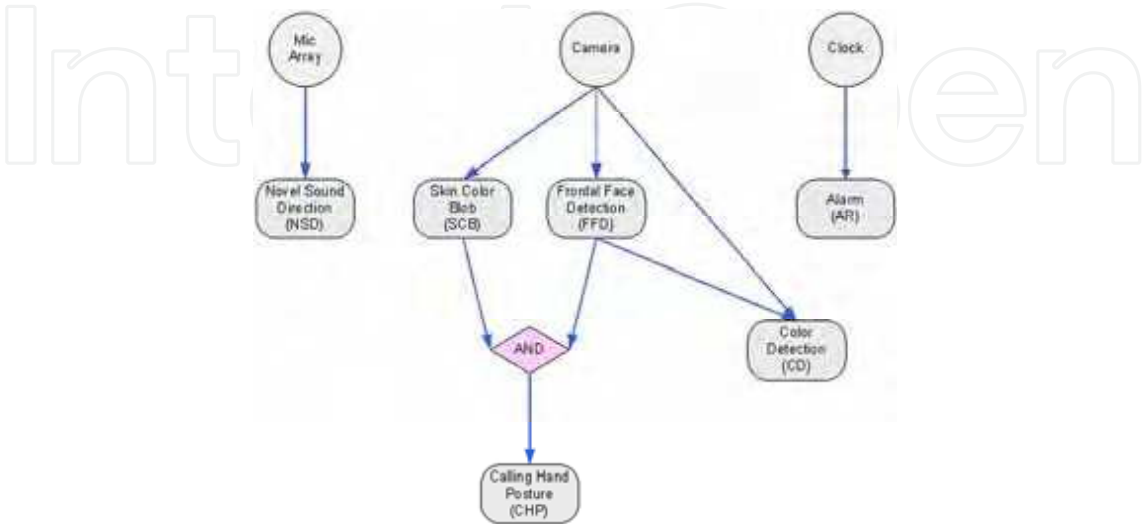
Figure 2. The precedence relation of all perceptual processes – All the relations without AND mean OR

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

4.1 Evidence Structure for the Robot Missions
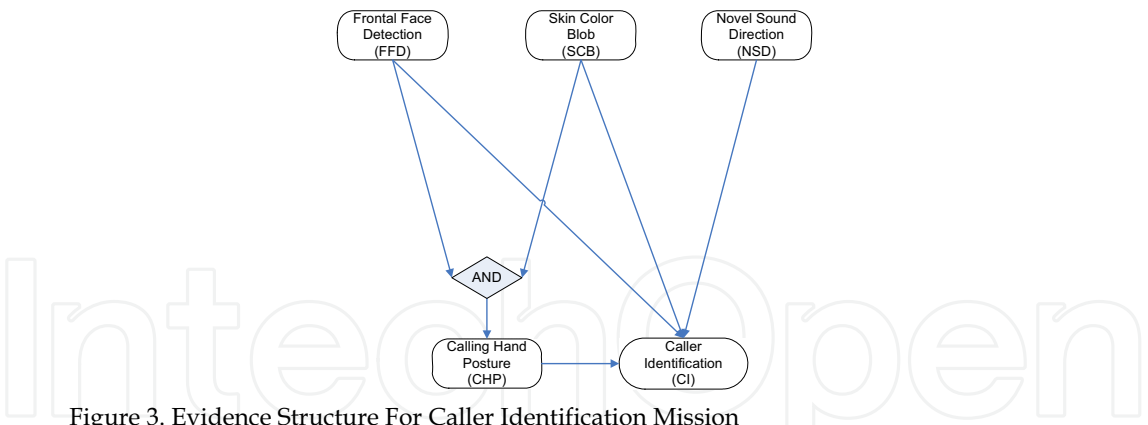
Figure 3. Evidence Structure For Caller Identification Mission

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.
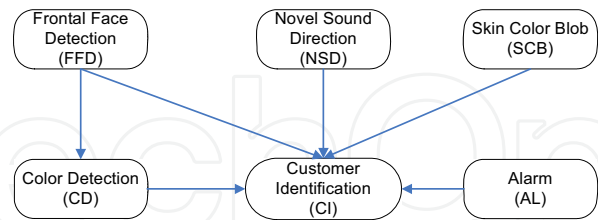
Figure 4. Evidence Structure For Customer Identification Mission
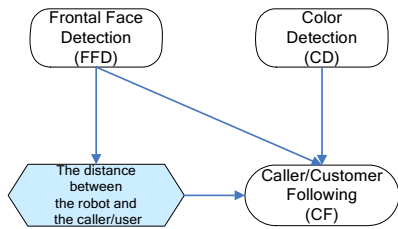
Figure 5. Evidence Structure For Caller/Customer Following Mission
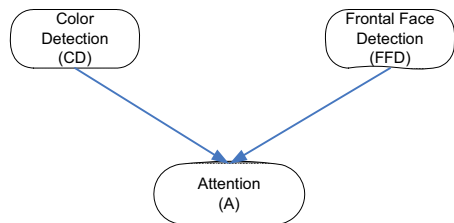
Figure 6. Evidence Structure For Attention Mission

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.

$$Mission\,Certainty\,(Mission)=$$

$$P(Mission\,|\,Evidences)=\frac{1}{1+\dfrac{P(Evidences\,|\,\overline{Mission})P(\overline{Mission})}{P(Evidences\,|\,Mission)P(Mission)}}=\frac{1}{1+\alpha} \tag{1}$$

$$\therefore\ \alpha=\frac{P(Evidences\,|\,\overline{Mission})P(\overline{Mission})}{P(Evidences\,|\,Mission)P(Mission)}$$

(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).

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

The rest α value of individual missions as follows:
- Customer identification

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

- Caller/Customer Following

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

- Attention

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

4.3 Certainty Estimation with Consider Space-Time
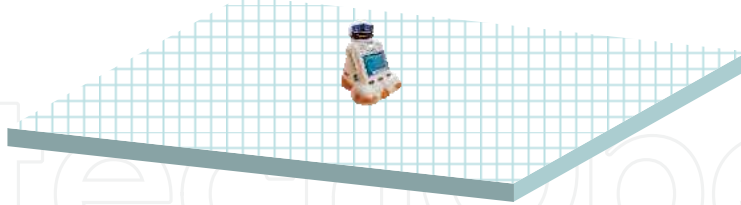
Figure 7. Interaction Space of the Robot for Certainty Representation

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 $\rightarrow$ ΔC(b1) = {Δc1(b1), Δc2(b1), … , Δck(b1), … Δcn(b1)}
b2 $\rightarrow$ ΔC(b2) = {Δc1(b2), Δc2(b2), … , Δck(b2), … Δ cn(b2)}
…
bk $\rightarrow$ ΔC(bk) = {Δc1(bk), Δ c2(bk), … Δck(bk), … , Δ cn(bk)}
…
bn $\rightarrow$ 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).

$$Selection\ of\ action =$$
$$b_{\max}\{P(callerID\,|\,Evidences + \Delta C_{b1}),...,P(callerID\,|\,Evidences + \Delta C_{bn})\} \qquad (6)$$

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
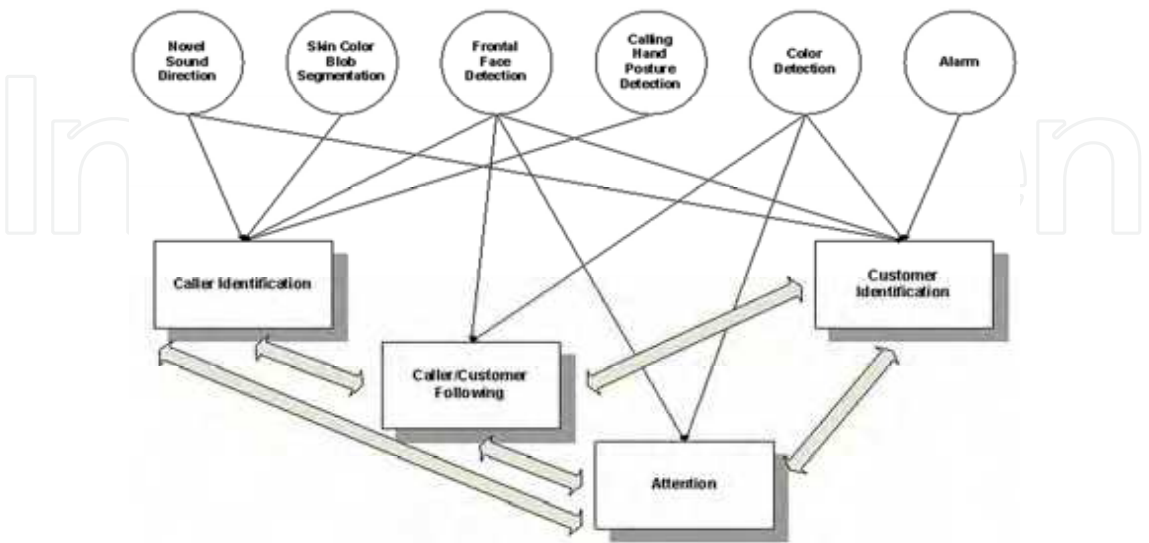6. With succeed/failure of the mission, the manager should change the state of robot naturally.

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

Figure 9. Robot Hardware

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.

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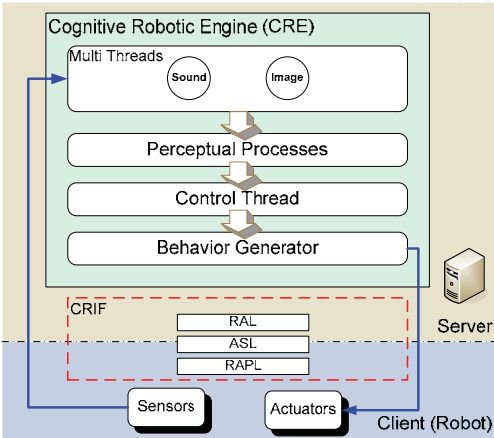
Figure 10. Overall Architecture of the System. (RAL: Robot API Layer, ASL: API Sync Layer, RAPL: Robot API Presentation Layer)

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.
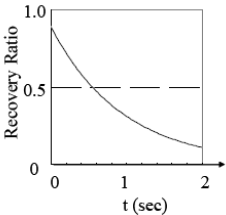
Figure 11. Forgetting curve of Brown Peterson paradigm

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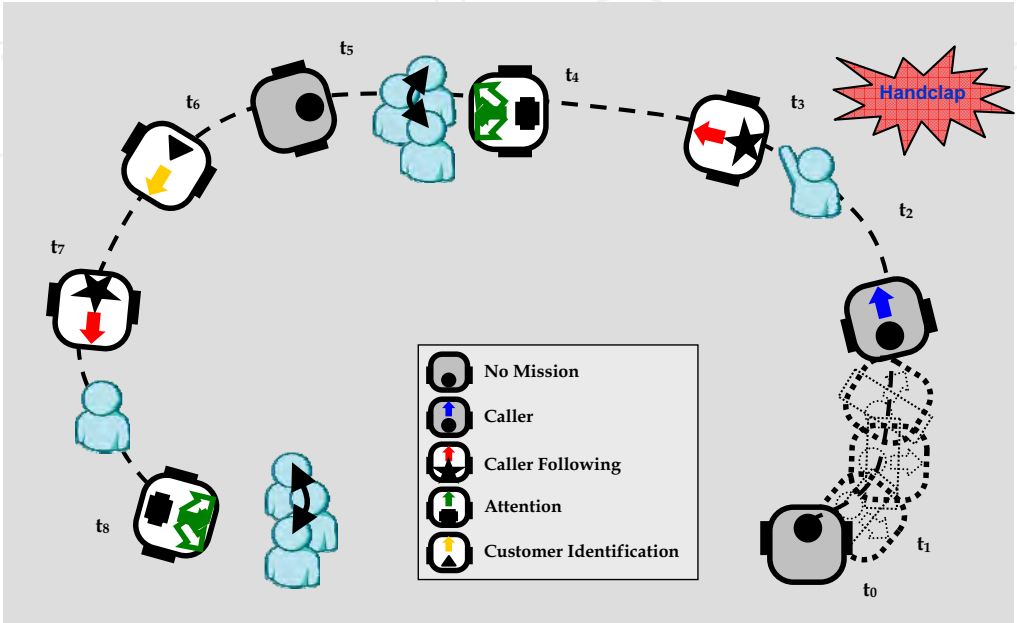
Figure 12. Experimentation of the multi-mission management and the certainty estimation of Cognitive Robotic Engine

8.2 Experiment Results

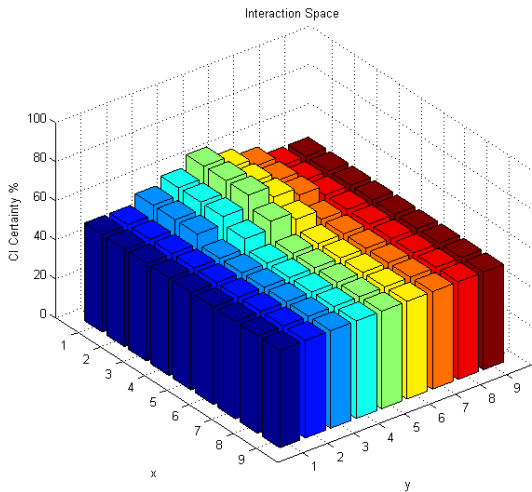Initially, control part of CRE enables only NSD , FFD, AL processes.

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

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).

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).
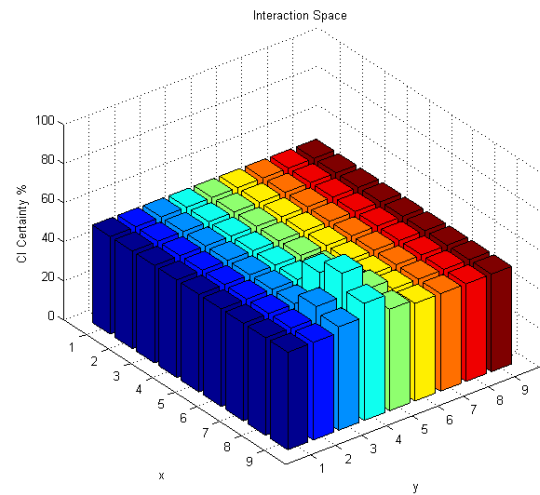
Figure 14. Certainty of the caller identification mission (t2, before calling hand posture detected)
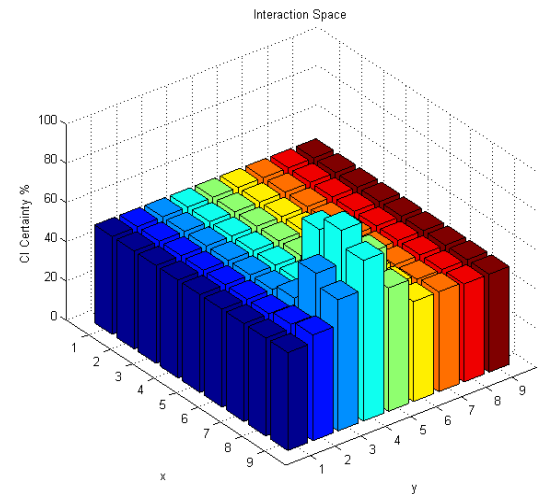
Figure 15. Certainty of the caller identification mission (t2, after calling hand posture detected))

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).
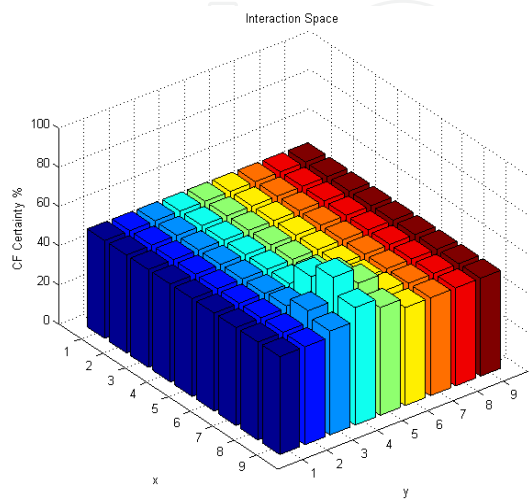
Figure 16. Certainty of the caller/customer tracking mission (t3)
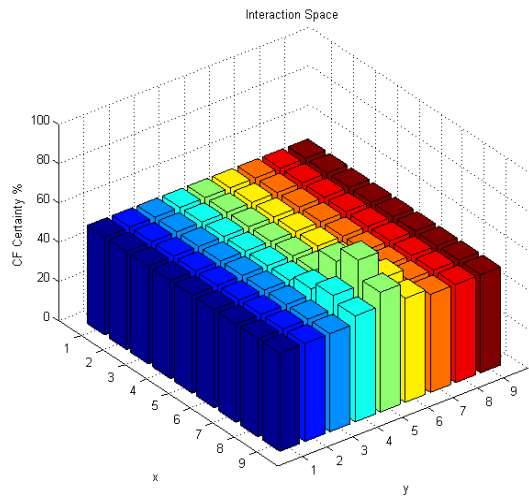
Figure 17. Certainty of the caller/customer tracking mission (t4)

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).
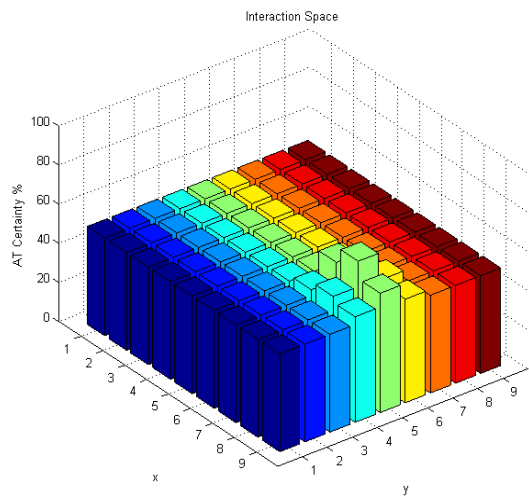
Figure 18. Certainty of the attention mission (t4)
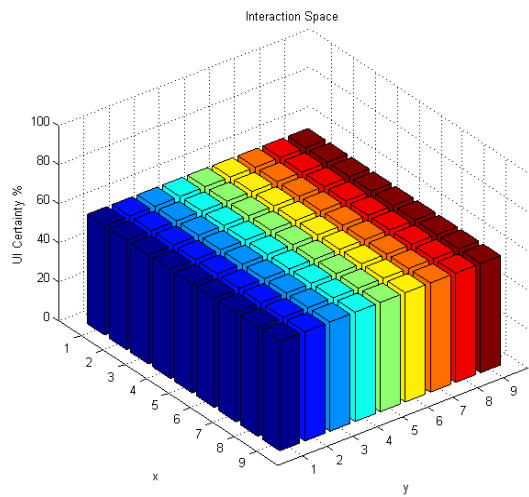
Figure 19. Certainty of the customer identification mission (t6)

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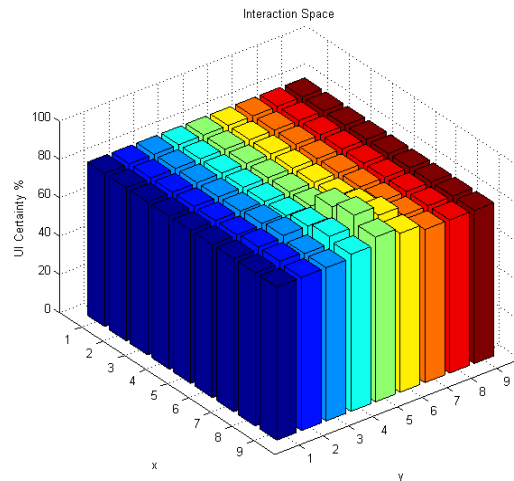
Figure 20. Certainty of the customer identification mission (t7)

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

11. References

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Human Robot Interaction

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Human-robot interaction research is diverse and covers a wide range of topics. All aspects of human factors and robotics are within the purview of HRI research so far as they provide insight into how to improve our understanding in developing effective tools, protocols, and systems to enhance HRI. For example, a significant research effort is being devoted to designing human-robot interface that makes it easier for the people to interact with robots. HRI is an extremely active research field where new and important work is being published at a fast pace. It is neither possible nor is it our intention to cover every important work in this important research field in one volume. However, we believe that HRI as a research field has matured enough to merit a compilation of the outstanding work in the field in the form of a book. This book, which presents outstanding work from the leading HRI researchers covering a wide spectrum of topics, is an effort to capture and present some of the important contributions in HRI in one volume. We hope that this book will benefit both experts and novice and provide a thorough understanding of the exciting field of HRI.

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