Cognitive Robotic Engine for HRI

Sukhan Lee, Hun-Sue Lee and Dong-Wook Shin

School of Information and Communication Engineering
Sungkyunkwan University
Suwon, KyungGi-Do, 440-746, Korea

lsh@ece.skku.ac.kr, smonkeys@hanmail.net, robotics@empal.com

***Abstract* – A "Cognitive Robotic Engine (CRE)" that generates perceptual and action behaviors to select and collect an optimal set of evidences has been introduced previously by the authors [1]. CRE aims at enabling a robot to be capable of dependable and robust recognition and decision under a high level of uncertainty and ambiguity in perception. This paper improves the performance of CRE based on the following expansion: 1) the provision of an evidence structure separately from the internal perceptual processes represented by a precedence graph, such that the contribution of individual evidences to the certainty of the premise pertaining to the given robotic mission can be more clearly defined, and 2) the establishment of a search process for action behaviors based on the overall contribution of the chosen action behaviors to the certainty of the premise pertaining to the given robotic mission. CRE is applied to the two robotic missions, caller identification and caller following, and is evaluated by actual experimentation. The experimental results show the expanded version of CRE results in improvement not only in dependability but also in stability.**

Index Terms – Perception, Action, Dependability, Cognitive Robotic Engine, Caller identification

I. INTRODUCTION

The issue of robot dependability is one of the critical factors why service robots remain in laboratories instead of transferring to commercial sectors. In contrast, human is quite dependable for perception based navigation and manipulation in spite of the fact that human perception may not always provide perfect information. Human dependability may be not so much to do with the quality of individual components that constitute perception or action. But, it may be much to do with an overall system behavior by which these individual components, regardless of how uncertain and imperfect they are, are coordinated into dependable system behaviors.

This paper aims at establishing a formalism of system architecture and control that implements such dependable system behaviors as human. We refer such a formalism to here as the Cognitive Robotic Engine (CRE).

A. Background

Dautenhahn [10] has listed different social relationships between robots and humans based on animal-human relationship. In recent years there has been a great deal of interest to develop algorithms and systems for human-robot interface, for instance see [2][8]. Most of these researches focused on the problem of proper response to the human while the reliable and dependable recognition and perception remains of a critical issue. On the other hand, the robot's hardware dependability has been under investigation for a long time, i.e. executing valid and safe commands, from the old industrial robots to the new mobile platforms. There are many examples of employing robots in public areas [7][11][12][13], such as museums and exhibition halls, in which dependability has been achieved by performing limited tasks trying to execute valid and safe commands which are verified in hard real-time. Fritsch et. al. [2] have proposed a system based on three layer architecture to provide a flexible infrastructure \suitable for human-robot interaction. The simpler interactions, such as gesture detection, are handled at the reactive layer while the sophisticated interactions, such as speech recognition and understanding, have been dealt with in the deliberative layer. Although the architecture allows incorporation of different human-robot interaction modules, however, it does not address handling uncertain situations in which the robot needs further information or clue to make an action.

II. CRE: OVERVIEW

In order to introduce the concept of CRE, let us consider how a human identifies a caller, if there is, dependably in 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. The 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.

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. The first key issue 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. In addition, human tends to take appropriate actions for gathering a better quality of or a new addition of information instead of depending passively on what is sensed for a decision. The second key issue may be 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. 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.

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 .

This paper extends our previous work on "Cognitive Robotic Engine (CRE)" [1] by improving the process for searching evidences and selecting actions.

III. Organization of Perceptual Processes and Action Processes

A. *A Precedence Relation of Perceptual Process*

A precedence relation of perceptual processes represents the input-output relationships of the individual processes defined as system building blocks. In other words, in CRE, a precedence relation implies a particular software configuration of individual perceptual processes or components designed for robotic missions. Fig. 1 shows a precedence relation designed for a robot engaged in a caller identification mission, where six perceptual processes, Novel Sound Direction Detector, Frontal Face Detector, Hand Detector, Skin Color Blob Detector, Calling Hand Posture Detector, and Caller Identifier, are defined to generate such evidences as Novel Sound Direction (NSD), Frontal Face (FF), Hand (HD), Skin Color Blob (SCB), Calling Hand Posture (CHP), and Caller Identification (CI), respectively, based on two sensor platforms, a micro phone array and a camera. The precedence relation among these six processes is shown by the flow arrows and logical AND/OR operation, where only AND operation is depicted explicitly in the figure. It indicates that the Calling Hand Posture Detector should wait for the outputs from both Frontal Face Detector and Skin Color Blob Detector and that the Caller Identifier should wait for one or any combination of the four processes as their inputs in order to produce their outputs. Processes with no precedence relationships explicitly specified can be run concurrently, if desired and allowed by the computational resources. Note that Caller Identifier, given as a mission, can use any combination of evidences from the four processes concurrently, if available.

Table I describes individual perceptual processes. Note that individual process independently and timely maintains four additional outputs except the evidences it generates, namely 1) the estimated and actual certainty factors of the evidences it generates (CF-E, CF-R), 2) the action candidates that can be invoked to improve the certainty factor of the evidences it generates (AC), 3) the estimated certainty factor of the evidences it generates after a relevant action candidate is assumed chosen and invoked (CF-A) and 4) the average processing time required to produce the evidences (PT). These additional attributes associated with individual processes are used to determine which perceptual processes and/or which action candidates associated with individual processes should be selected for reaching the decision on caller identification effectively and efficiently for CRE.

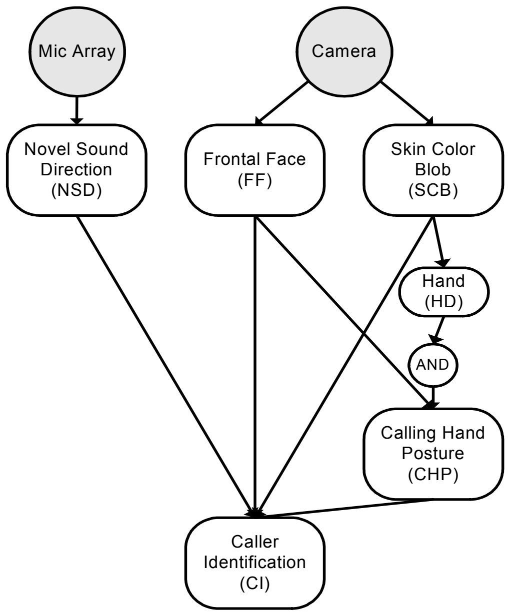


Fig. 1 The precedence relation of perceptual processes for a mission of caller identification – All the relations without AND means OR.

TABLE I
DESCRIPTION OF PERCEPTUAL PROCESSES FOR CALLER IDENTIFICATION

NSD	**Def.**	When the sound volume exceeds the threshold, estimates the direction of source
	Source	Mic Array
	Input	Raw data of sound
	Output	Direction of novel sound Estimated Certainty (CF-E) Present Certainty (CF-R) Expected Certainty(CF-A) Candidate of action (AC) Processing Time (PT)
FFD	**Def.**	Finds face region by image feature
	Source	Camera
	Input	Raw image from Camera
	Output	Coordinate, and size of detected face CF-E, CF-R, CF-A, AC, PT
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-E, CF-R, CF-A, AC, PT
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-E, CF-R, CF-A, AC, PT

B. *Evidence Structure*

CRE aims at combining or fusing multiple evidences in time for dependable decision. The evidences to be fused are chosen from the list of evidences that can be offered by the individual perceptual processes with or without taking the actions for collecting better certainty of evidences into consideration. In order for the system to automatically determine the processes and/or actions that supply the evidences to be fused, we need to know how individual evidences and their certainty factors contribute to the certainty factor of the decision for the given mission. For this purpose, we define an evidence structure describing the logical relations of individual evidences. For instance, for the caller identification mission, the evidences provided by individual processes can be structured based on the following causal relationships:

$$
\begin{aligned}
&\mathit{CallingHandPosture} \rightarrow \mathit{CallerID}\\
&\mathit{NovelSoundDirection} \wedge \mathit{FrontalFace\ at\ NovelSoundDirection} \rightarrow \mathit{CallerID}\\
&\mathit{FrontalFace} \wedge \mathit{Hand\ at\ theLeft/Rightside\ of\ FrontalFace} \rightarrow \mathit{CallingHandPosture}\\
&\mathit{FrontalFace} \rightarrow \mathit{SkinColorBlob}\\
&\mathit{Hand} \rightarrow \mathit{SkinColorBlob}
\end{aligned} \quad (1)
$$

Fig. 2 illustrates the above logical relationships among evidences in a graphical form. The evidence structure described by (1) and Fig. 2 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 [19].

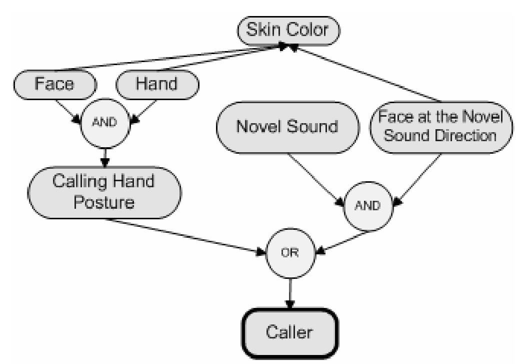


Fig. 2 Evidence structure for a mission of caller identification

C. *Organization of Action Processes*

The robot actions for collecting better evidences can be organized in terms of simple actions that are mutually exclusive, such as head and base motion based actions and verbally oriented actions, and of compound actions as a combination of simple actions. Similar to our previous approach [1], we define Look Around (LA) and Heading (HE) as head motion based actions, Wandering (WA), Approaching (AP), Turning (TU) as base motion based actions, and Verbal Inquiry (VI) as a verbally oriented action. As for a compound action, we define a Searching (SE) action as a random combination of LA and WA. This is illustrated by Table II. Note that we simplified the number of actions so as to observe their effect on actual robot behaviors more clearly. For more details of the definition of each action in Table II, refer to [1]. Note that the actions defined here are connected to individual perceptual processes in which the candidate actions for improving the certainty factor of the corresponding evidences are defined.

TABLE II
A list of candidate actions for caller identification

Action Classes	Unit Actions
Head Action	Look around (LA) Heading (HE)
Base Action	Wandering (WA) Approaching (AP) Turning (TU)
Verbal Action	Verbal Inquiry (VI)
Compound Action	Searching (SE)

IV. Control for Choosing an Optimal Set of Evidences

Under CRE, a mission is invoked whenever the evidences from the constant influx of sensory data push the certainty factor of the mission evidence up over a certain threshold. For instance, initially, Robot may wander around with its sensory channels open to environment and its perceptual processes generating evidences and updating their certainty factors asynchronously and concurrently in a bottom-up manner. Robot may stop wandering around and invoke a mission, such as the caller ID mission, as soon as the evidences may suggest someone calling, i.e., the certainty factor of the caller ID evidence exceeds a certain threshold. Upon the certainty factor of caller ID evidence exceeds a predefined threshold, Robot registers the mission., "Caller Identification," on its mission queue and immediately starts to engage in the behavior for verifying whether there indeed is a caller or not. The caller ID mission will remain in the queue till the above verification is completed. Once invoked, Robot seeks for additional evidences in such a way as to reach a conclusion as dependably and efficiently as possible under the limited computational resources. This is done by planning which additional processes be activated to generate more evidences and/or which actions be initiated to collect better quality of evidences.

The selection of additional evidences is based on the contribution of the candidate evidence to the certainty factor of the mission evidence for decision, either positive or negative, in trade-off with the time, energy and computational resources to be expended for processing. Note that each perceptual process defined for CRE is supposed to output the estimated and actual certainty factors of the evidences it generates. The certainty factor of the evidence generated by a process depends on the situation Robot is under, since sensor performance varies to the environmental variations, including the variations in measurement distance and orientation as well in illumination. Robot is assumed to be able to monitor these variations, such that the certainty factor of the evidences generated by a process can be estimated and kept updated. Note also that a process has a list of candidate actions recommended to take if higher certainty factor of evidences are required. Robot is assumed to keep monitoring the situation it resides, such that the certainty factor of the evidences after an action is taken can be estimated.

Once the certainty factors of individual evidences are estimated, the contribution of particular evidence to the certainty factors of the mission evidence can be computed based on the evidence structure. The control unit is responsible for selecting an optimal set of evidences to collect from perceptual processes with/without actions by evaluating its quality in terms of the trade-off between the contribution to the certainty factor and the cost due to required time and energy under limited resources. Note that this search process can be very complicated depending on the scope of the optimality we pursue, since 1) the perceptual processes are run in an asynchronous and concurrent manner with different processing time, 2) as mentioned, the certainty factors of evidences associated with individual processes vary according to the situations Robot face against environment, 3) the number of possible combination of evidences to be considered in search may increase exponentially as CRE is applied to a complex structure of missions and of perceptual processes and actions, and 4) the breadth and depth of search can vary according to the degree of optimality we pursue under the limited computational resources, the predefined precedence relations, and the evidence structure.. Here, instead of exploring the full scope of optimal search, we assume that the computational resources are sufficient enough to allow a full concurrency under the predefined precedence relation of perceptual processes. Then, the control problem becomes the selection of a feasible yet optimal set of actions that offer best contribution to the certainty factors of Caller ID evidence in unit time. As shown previously, Robot can take multiple actions simultaneously as long as they are mutually exclusive.

A. *The Certainty Factor associated with the Mission*

The certainty factor associated with the mission should be updated in time as evidences are accumulated. For instance, a novel sound may increase the certainty factor of the caller ID over a threshold and invoke the caller ID mission. To verify the truth of the mission, CRE may seek for such additional evidences as Frontal Face in the direction of Novel Sound, Calling Hand Gesture, etc. with or without actions like Approaching to Novel Sound Direction, Verbal Inquiry, etc. to update the certainty factor of the mission. The update of the certainty factor can be done by applying the Bayesian posterior probability theorem to the evidence structure for evidence fusion and the filtering in time for evidence accumulation:

$$\text{Mission\_Certainty}(CallerID) = P(CallerID \mid Evidences) = \frac{1}{1+\frac{P(Evidences \mid \overline{CallerID})P(\overline{CallerID})}{P(Evidences \mid CallerID)P(CallerID)}} \quad (2)$$

(2) shows that the probability of Caller ID, represented as the certainty factor of Caller ID, given a set of evidences can be computed by estimating the probabilities of a set of evidences when caller ID is and is not assumed as well as the prior probabilities of caller ID and no caller ID. Note that at time *t*, the certainty factor of evidence, represented as the probability that the evidence is true for the given sensing, propagates through the evidence structure defined previously to update other evidences. This can be done by using the Bayesian net update procedure by interpreting the evidence structure in terms of a Bayesian net. However, each evidence is subject to a certain degradation of its certainty factor as time passes, where the degradation is determined by the temporal correlation of evidence. For instance, assuming Frontal Face is detected at time t with a certain certainty factor, the certainty factor of Frontal Face at time *t+1* may be degraded from that of time t according to the tracking uncertainty if tracking is applied or degraded significantly if no tracking is applied, etc.

B. Selection of Actions

Previously, we chose to select the actions that are recommended by the perceptual process that generates the highest certainty factor of evidence [1]. However, we observed that this resulted in frequent and sudden changes of different actions in time and made Robot appear unstable in its behavior. This was due to the fact that there were no accumulation of certainty factor in time as well as no direct contribution to the mission evidence. Here, the selection of actions at each sampling time depends on the contribution of individual action to the certainty factor of the mission in trade-off with the time and energy required for the action, as mentioned previously. For instance, if the caller identification mission must follow the approaching to the caller for a service, the action, Approaching, does not cost additional energy. Also, two actions defined based on head and base motions respectively can be activated simultaneously, since they are mutually exclusive.

V. Implementation of Hardware and Software Architecture

A. Hardware Specification

The approach outlined above has been implemented on the mobile robot shown in Fig. 3. The specification of single-board-computer has Intel Pentium mobile processor 1.40GHz, 1GB RAM, and 40GB hard disk. Bumblebee camera as imaging sensor is approximately 160*40*50mm size with 70° horizontal-field-of-view(HFOV) and 640*480 square pixels at 30Hz/1024*768 square pixels at 15Hz. In this implementation, we used only right image of camera with 320*240 resolutions.

Fig. 3 iRobi: a home robot for education and security, used for implementation of CRE [the courtesy of Yujin Robotics Co Ltd.]

B. System Architecture and Software Design

Overall architecture of CRE system is presented in Fig. 4. Robot/hardware-dependant procedures are implemented in robot platform. On the other hand, hardware independent procedures are implemented in the server so that CRE system could be adapted to another platform easily. The robot and the server communicate by TCP/IP socket. 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. All the results from perceptual processes are reported by the packet form. The contents of packet are shown in Table III.

Each process has its suggestion of actions to get more evidences from the environment. Refer to Table II, Table IV represent the actions from a process depends on the amount of uncertainty. Any action which is selected will heighten the mission certainty and the best action that makes the highest mission certainty will be chosen.

C. Implementation of Caller Following Mission

As the first step, mission of caller following is implemented simply. In the previous work, we defined a mission of caller identification as identifying and approaching to a caller. This results in some ambiguities of action, i.e., the hesitation even the robot certainly found a caller. So we distinguished a caller following mission from the previous one. When robot identifies a caller, there is always a face in our assumption. Based on the detected face, we get the tracking point in the image and attentively approach to the object.

D. Sampling Time of Control

There can be several approaches for the control. In psychology field [16][17][18], there is a forgetting curve of Brown Peterson paradigm which is concerning about human short term memory. It is shown in Fig. 5. Based on that curve, we decided the sampling time as 600ms approximately.

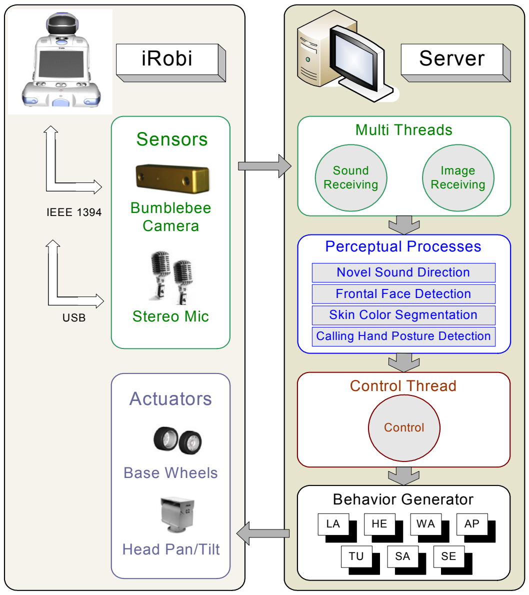


Fig. 4 The architecture design of CRE implementation on iRobi

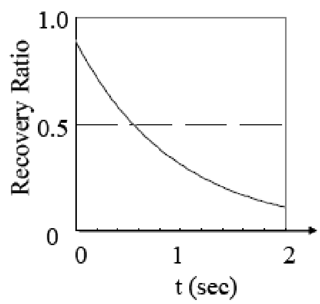


Fig. 5 Forgetting curve of Brown Peterson paradigm

TABLE III

The contents of packet for caller identification

Data Name	Size (byte)	Description
name	2	The name of perceptual process
n_data	4	The size of packet
time	8	Time when packet sent (ms)
cur_cert	4	Uncertainty measure
behavior	2	Suggested behavior
size	4	Detail information of result from process
x	4	
y	4	
theta	4	

TABLE IV

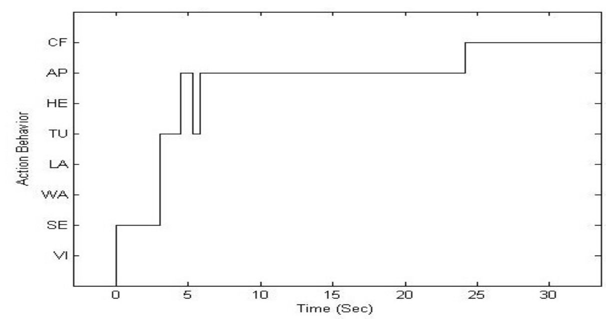
Description of candidate actions from perception processes

Process	Certainty level	Candidate actions
NSD	Low	Verbal Inquiry, Look Around
	High	Heading, Turning
FFD	Low	Heading
	High	Approaching
SCS	Low	Searching
	High	Heading
CHP	Low	Look around
	High	Approaching

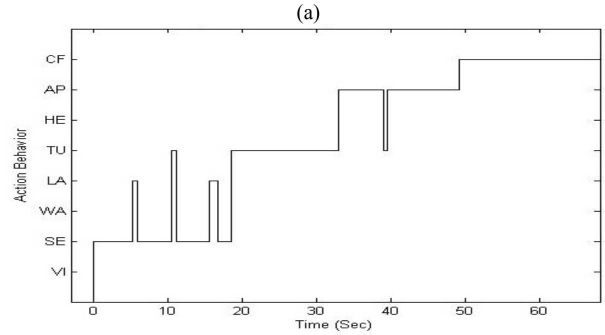
VI. Experimental Results

In this section, we present some preliminary simulation experiments which indicate that proposed CRE provides more natural human-robot interaction.

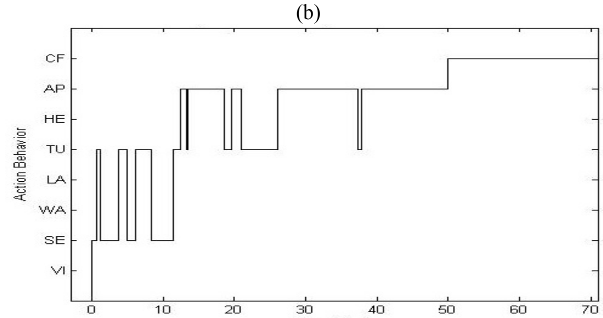
Our experiments focus on the observation of robot's behaviors. Fig. 6 shows the action-transition diagram of the robot. Fig. 6(a) shows the simple case of caller identification. As soon as the robot began to search the caller, an evidence of skin color blob made the robot turn, then the robot found human face. The caller was detected with his calling hand and the robot followed him. In Fig. 6(b), robot looked around or turned to the direction of novel sound several times. But robot started to search a caller again since there wasn't exists a caller. In Fig. 6(d), robot found the human-face several times. It approached to the human, however, he wasn't a caller. Next time, the robot turned to the other side to find a caller, and then identified a caller. Fig. 6(e) shows the case when a caller identification is done by human face and novel sound. Although there was no calling hand posture, evidences of detected face and the novel sound at the direction were fused.



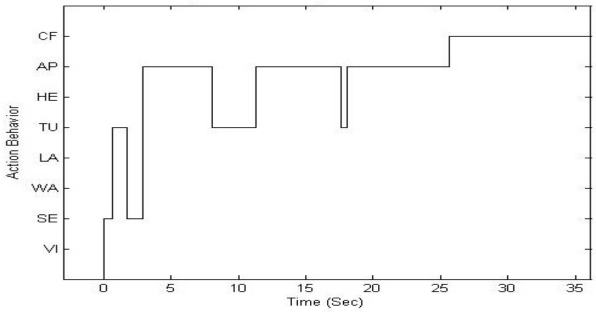
(a)



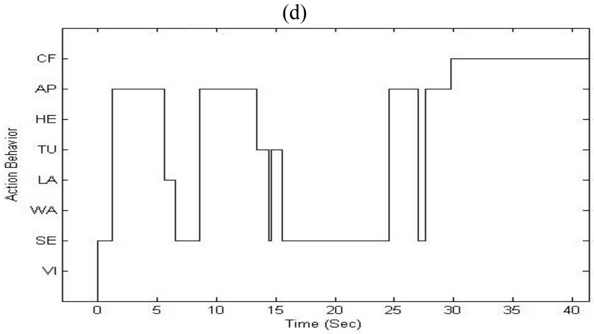
(b)



(c)



(d)



(e)

Fig. 6 Action transition diagram during caller identification and caller following

This result shows the robot was able to identify a caller even the robot sometimes missed the human. Different kinds of evidences are collected for the estimation of control. The proactive actions invoked to accomplish the mission were observed.

VII. Discussion and Conclusion

In summary, we have extended previous work i.e., the introduction of CRE concept by mission control by uncertainty measurement, evidence collection with action and maintaining behaviors. Primitive sensing data are generated from asynchronous and concurrent perceptual processes and control judges the mission certainty based on the outputs from the processes by Bayesian. Proactive actions were taken to complete the mission of caller identification. Then the robot performed the mission of caller following successfully. This approach can be an alternative way to control a robot, rather than the conventional approaches.

Although the concept of CRE is supposed to be robust in noisy environments, the experimental design was rather simple due to the implementation and small number of mission. Moreover, the estimation of given mission considering processing resources is also remained as a key issue.

Acknowledgment

This work is supported by the "Ubiquitous Robotic Companion (URC) Project" sponsored by the Ministry of Information and Communications (MIC). The authors would like to thanks the Yujin robotics co. Ltd for providing their home service robot, iRobi. Also the Authors would like to thanks Mr. Jangwon Lee for his help for the menu script and experimentation.

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