Design of Co-Adaptive Interface System for Supporting Joint Task by Human and Machine Autonomies

Yukio Horiguchi

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Acknowledgments

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Abstract

Toward the making of "human and technology ensembles", their communication is one of the most critical elements to bridge gaps between them. Human-machine interaction design is to give automated systems a kind of *sociality* to their human partners. Concerning this issue, this dissertation encloses the research works performed from a new perspective of "co-adaptive interface" for effective human-machine systems. Each work is presented after the reviews of the problems and challenges of human-machine systems design to date, and all of them focus on the relationship between humans and machine autonomies.

Chapter 2 explains the basic approach of this dissertation to the human-machine interaction design issues, and then introduces a new concept of co-adaptive interface that facilitates mutual adaptation processes between humans and machines.

Chapter 3 examines the feasibility of the facilitating systems which can mediate the interaction between a human operator and a teleoperator robot, by introducing a new concept of *intertask morphology* or the *isomorphism* between two different tasks. The concept of intertask morphology in human-machine systems aims at connecting two different behavioral tasks via their structural isomorphism, and extending the operator's actual perception-action cycles to the ideal perception-action cycles with his/her distal attribution established.

Chapter 4 investigates operational skills of human operators to explore the necessary information resources to be externalized in tele-operation environments, focusing on *externalization*, or the act performed to uncover hidden structures in the work domain onto the surface. The skill analysis is done from two perspectives: the one is on how skillful operational strategies organize the robotic behaviors to make the necessary but hidden information externalized onto the display; and the other is on how different operational strategies exhibit different manners of practicing the search procedures.

Chapter 5 provides a formal approach to designing human-machine interaction channels between a human operator and a machine autonomy. A shared-control environment by a human operator and an autonomous mobile robot is investigated based upon the classification of information types defined in Kirlik's *Generalized Lens Model* framework. After this analysis, a new human-robot collaboration style is proposed with the *shared communicational modality* between the human opera-

tors and the robot autonomy.

Chapter 6 addresses the adaptability in the human-machine collaboration as a necessary element for the adequate coordination between human and mechanized control. Inspired by our human proactive actions to the external world, the author advocates to introduce proactive agency into the machine autonomy so that it can probe or sound out the partner's *covert* judgments for its adaptation. This behavioral model is evaluated using a simulated shared-control environment, and then the discussion is made about feasibility of the *co*-adaptive approach towards the well-coordinated collaboration by the human operator and the robot autonomy.

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Chapter 1

Introduction

Modern automation technologies embody a lot of intelligent controls in a wide variety of mechanical systems, ranging from everyday gadgets to safety-critical sectors, including cellular phones, VCRs, automobiles, health-care or medical devices, aircraft, and advanced manufacturing plants. They make our lives more efficient by giving us impressive functionality and unprecedented access to information. Therefore, we rely on them now, and also will rely on them much more in the future. In other words, "our dependence on those technologies already influences who we are and who our progeny will be" [16, p. 39].

On the one hand, automation plays an important role in governing large-scale complex systems like aviation aircraft, electric power plants, and so forth. Autopilots for aircraft can accomplish their mission autonomously without any or with minimal input from human operators. Already airplanes can be flown over long distances with multiple course changes, entirely by computer. They can even take off and land automatically (although current flight rules prohibit it). Airline pilots depend on them to land safely, especially in bad weather.

On the other hand, the application fields of such automation technologies are rapidly enlarging to our near affairs like cars. For instance, ABS (Antilock Braking System) can prevent the brakes from locking up and skidding during emergency braking or when the brakes are overheated. The system electronically monitors the speed of the wheels and regulates the hydraulic pressure accordingly so as to maximize braking power. Latest luxury cars are also being equipped with ACC (Adaptive Cruise Control), which allows our car to follow the car in front of it while continually adjusting speed to maintain a safe distance. Even though you have not touch the brake or gas pedal, the technology makes this adjustment autonomously, by utilizing forward-looking radar installed behind the grill of a vehicle to detect the speed and distance of the vehicle ahead of it.

As exemplified above, various kinds of automation are running in and around our everyday lives whether we might be aware of their business or not. Many human functions have been becoming automated so far. As technology evolves and becomes more available, we will give machines more and more authority to take over and sometimes even override our own commands in order to keep the systems safe. The ultimate application of these technologies may be to seize control of the system completely.

However, it's true that complexity of tasks and an uncertain or changing operating environment bring about technical issues of inability to automate certain aspects of the system. That is, human judgment is necessary for the unpredictable events in which some action must be taken to preserve safety, to avoid expensive failures, or to increase product quality, as Shneiderman noted:

> "The degree of automation will increase over the years as procedures become more standardized, hardware reliability increases, and software verification and validation improves. With routine tasks, automation is preferred, since the potential for error may be reduced. However, I believe that there will always be a critical human role, because the real world is an *open system* (there is a nondenumerable number of unpredictable events and system failures). By contrast, computers constitute a *closed system* (there is only a denumerable number of normal and failure situations that can be accommodated in hardware and software). Human judgment is necessary for the unpredictable events in which some action must be taken to preserve safety, to avoid expensive failures, or to increase product quality (Hancock and Scallen, 1996)." [49, p. 83]

Even when full autonomy was possible, there should also exist a lot of demands to allow for human judgments, such as safety, training, maintenance, calibration and so on. It is inevitable to ask for human interventions even though the automated systems are well tailored in great detail. Human will remain. Hence, automation needs to behave in harmony with human. The two must work together.

At this point, human and technology should be understood as integral part of the entire system wherein they are mutually related. Toward the making of "human and technology ensembles", their communication is the most critical element to bridge gaps between them. Human-machine interaction design is to give automated systems a kind of *sociality* to their partners. As a concept of "human-centered automation" [3, 56], or a philosophy that guides the design of automated systems in a way that both enhances system safety and efficiency and optimizes the contribution of human operators, reveals, automation needs to behave *socially*: the system recognizes people as intelligent agents it can (or must) inform and be informed by. In contrast, traditional "black box" autonomous systems execute prewritten commands and generally treat people in their environments as objects if they recognize those at all. That is to say, they have no means of relating to us. Such technologies are well tailored to the physical world but too complex for human users to handle.

1.1 Potential Straggles between Human and Machine Autonomies

Many modern devices and facilities are composed of large numbers of subsystems, and their interaction may lead the whole system into undesirable states even where the behavior of each subsystem is well understood in isolation. Wherein, introducing some alternate components will cause other changes in the individual subsystems, all of which compose the dynamics of the system. Sometimes such dynamics may be too complex even for designers to fully understand all the possible ways the system can behave. Their inherent complexity makes it difficult for users to understand, supervise and interact with automated systems properly, and the fact gives proof of it that the designers cannot always account for every possible system outcome. This unpredictability of the autonomous behaviors from the user's point of view is represented as *non-determinism* [7], which refers to a system that behaves in a way that cannot be determined. They confuse us, and therefore are quite dangerous at times, especially when we have no way of "communicating" with them.

For example, a horrible accident that resulted from struggle between human (the pilots of a large modern airliner) and automation (the aircraft's autopilot) took place over Nagoya Airport, Japan in 1994:

> "During the approach to the runway, the copilot, who was flying the aircraft manually, mistakenly engaged the GO-AROUND mode. The autopilot immediately commanded the aircraft to climb and go around. The copilot, however, wanted to continue the landing and was pushing the control wheel down. The more the copilot pushed down, the more the autopilot countered and adjusted the aircraft's control surfaces for climb. In a struggle between man and machine, the autopilot eventually won; it had more control authority. But at the end of this duel everyone lost. The aircraft stalled and crashed on the runway." [7, pp. 35–36]

A common purpose of automation is, in principle, to alleviate physical or mental labor of human operators while, at the same time, to increase the precision and economy of operations. We will, however, fail to recognize the actual relationship between our own operational commands and their results if automated control executes its functions in a way that we cannot understand it. And to make matters worse, the automated system might produce outcomes that are not relate to our intent. When such procedures have done without our realizing, it is much more difficult for us to figure out the proper causality on our operations. This kind of experiences will make us feel that the machines seem to act as if they have a mind of their own, and that we have no locus of control over the system.

As the complexity of technology increases, so does the sophistication of the human-machine coalition required to support and control it effectively [53]. And then, highly autonomous systems have a strong requirement for effective interaction with human operators.

1.2 Challenges of Designing Human-Machine Interaction

1.2.1 Designing "Transparent" Task Ecology

In order to facilitate human operators accurately exploiting complex mechanical systems, their work environment should be *transparent* [54]; the environment needs to be well structured so as to create the phenomenological feeling in the operators that they are "directly" monitoring and controlling the functions of the system, not dealing with the intermediary processes and elements [52]. That is to say, the essential goal of human interface design is to effectively support human operators concentrating their mind on what they really want to do by a mechanical instrument, not on how they needs to do with the instruments itself.

By nature, human cognition is best studied not as individualistic mental phenomenon, or information processing occurring inside the brain of a solitary thinker. Instead, it is necessary to consider cognition as "a joint activity involving several agents, some human and other technological" [58]. Hutchins has made explicit the unit of cognitive analysis as a network of people and technologies, and this perspective of the anthropology is known as a concept of *distributed cognition* [21,22]. Considering human-machine interaction designs from this point of view, human interface systems play an important role as cognitive resources for human decisions. If the interface can only provide impoverished information on the internal functions of the system, the human operators have to assimilate its actual complexity inherent of the intermediary processes; inference may be needed to compensate for the decrease in information availability. The more complexity of the system increases, the more internal cognitive resources and behavioral adaptations of the operators are required. It will cause collapses in the human-machine coalition at last.

Concerning this issue, Vicente and Rasmussen argue that the interface design should be isomorphic with the way humans think and operate. They have called for human-machine interface design to be *ecological* (i.e., *ecological interface design* or EID), meaning that "to properly control the process, the human-machine system must take account, or embody, the constraints inherent in the work domain" [54,55]. Wherein, the task environment around the system controlled is first portrayed as a functional decomposition by the means-end hierarchy. This careful task analysis figures out the inherent structure or semantics of the work domain, and specifies the content and structure of the interface. And then, in order to "make visible the invisible", this semantics of the task ecology is mapped onto the geometry of the display components in a way that exploits "direct perception". By enabling the operators to act on the display directly, EID supports human interaction with the system via the perception-action cycles, instead of the chain of inferences to compensate for the decrease in information availability that demands the operators' conscious efforts so far.

1.2.2 Designing "Social Skill" of Machine Autonomy

On the other hand, it is impossible for human operators to seize complete control all over the internal functions in such complex mechanical systems because of their inherent and increasing complexity. They can, so to say, behave independently of humans on some level, and can be regarded as the collaboration partners beyond instruments. Automation to date, however, has no means of relating to human operators as Sheridan has pointed out:

> "Automation is still foreign to most people, though. They don't understand it. The most sophisticated it gets, the less they understand it. When they don't understand it, they may trust it. Or they may overtrust it, attributing to it intelligence that it really does not have. Automation is silent and opaque. It does not reveal its intentions. The people around it cannot always predict what it is doing at the moment or what it is going to do next.
>
> Automation is mostly stupid and single-minded. Unlike people, it is not robust and adaptable. It does what it is programmed to do, which is not always what is desirable or even when the humans using it or affected by it expect it to do." [48, p. 12]

That is, today's automated systems "close-mindedly" execute what they are programmed to do, indifferent to how correctly their partners are aware of what they are doing and what they are going to do. Therefore, all efforts to resolve mismatch between human and automation are charged only to humans, and it may, at times, induce a new type of human errors known as *automation surprises* [38, 57] in aviation. From this perspective, we need to develop adaptive systems in which human and machine can operate together harmoniously.

Several researchers are approaching to this challenging problem in terms of "adaptability" embedded in human-machine systems. Some research works are related to "function allocation" between humans and machine. For instance, Scallen and Hancock [43,44] have advocated adaptive function allocation, in which the control of tasks dynamically shifts between humans and machines, as an alternative to traditional static allocation, in which task control is assigned during system design and remains unchanged during operations. Other works focus on adjustment of machine autonomy, i.e., *adjustable autonomy*. Adjustable autonomy refers to entities dynamically adjusting their own "level of autonomy" [32,47] based on the situation.

This idea still remains at the conceptual, but has been deployed to some emerging application areas like a multi-agent system assisting a research group in its daily activities [45], human-robot teamwork in long term space missions [8, 50], and so on. Note, however, that understanding these approaches to realizing adaptive human-machine systems is limited by sparse systematic research and an underdeveloped theoretical framework for implementation.

1.3 Contributions of The Dissertation

The author is approaching to the issues mentioned above from the perspective of "co-evolutionary human-machine systems" [16] by introducing a new concept of "co-adaptive" interface that can facilitate mutual adaptation processes between humans and machines.

The height of human-machine collaboration is the point at that the machine becomes *transparent* in its user's consciousness; the machine becomes integrated as the user's extended body. Unavoidably, however, deviations from such a well-coordinated relationship between the machine and the user will sometimes appear, no matter how deliberately the system is designed. Recovery and outgrow from this bottom require some "conversations" towards the agreement between the two entities. Although something competitive and conflictive between them will arise in the process, such an ideal state of collaboration is always formed and reformed through experiencing the conflicts and by introspecting the competitions.

Therefore, good human-machine interfaces should provide some bilateral information channels, through which both humans and machines can exchange their exploratory acts to adjust their judgments to each other. Dynamic interactions through those bilateral information channels would shape the flexible or ever-changing collaboration with adequate mutual dependency and reciprocity between the machine and the user.

Toward the embodiment of this design concept, this dissertation contributes in the following senses:

- presenting fundamentals of task analysis on the ground of isomorphism for transparent human-machine relationships (Chapter 3);

- providing a new systematic approach to designing effective communication channels, through which their exploratory acts are exchanged between a human operator and a machine autonomy (Chapter 5);

- proposing a new behavioral model of autonomy adaptation, which sustains the flexible or ever-changing collaborations in human-machine joint activities (Chapter 6); and

- addressing the other element in the human-machine equation, i.e., human skills and their adaptation (Chapter 4).

1.4 Organization of The Dissertation

The followings are general descriptions of the contents of the individual chapters.

Chapter 2 explains the basic approach of this dissertation to the human-machine interaction design issues, and then introduces a new concept of co-adaptive interface that facilitates mutual adaptation processes between humans and machines.

Chapter 3 examines the feasibility of the facilitating systems which can mediate the interaction between a human operator and a teleoperator robot, by introducing a new concept of "intertask morphology" or the *isomorphism* between two different tasks. The ideal human-machine interface system can facilitate the human operator's attribution to the distal events in the remote location (i.e., "distal attribution"), and will create the phenomenological feeling in the operators that they are directly monitoring and controlling the functions of the system. The concept of intertask morphology in human-machine systems aims at connecting two different behavioral tasks via their structural isomorphism, and extending the operator's actual perception-action cycles to the ideal perception-action cycles with his/her distal attribution established. From the perspective of this idea, careful analyses have been done to find out the invariant structures that are common between two behavioral tasks in a VR-based (i.e., virtual reality based) tele-operation; the one task was configured in the VR space while the other was done in the real world. These two tasks are analyzed as both decomposed into four qualitatively different phases, suggesting the potential of the behavioral mapping between them.

Chapter 4 investigates operational skills of human operators so as to explore the necessary information resources to be externalized in tele-operation environments. Tele-operation environments are indirect systems whose communicational and mechanical bandwidth restricts the human operators' perception-action cycles towards the distal events; they put bounds to the amount and quality of the perceptual information available as well as the practicable operations. Therefore, the operators confront with the considerable difficulties in developing the accurate situation awareness of the remote site and making the appropriate responses to the situations. In order to approach this issue, skillful operational strategies acquired to compensate those unnatural conditions are analyzed in terms of "externalization", or the act performed to uncover hidden structures in the work domain onto the surface. The skill analysis is done from two points of views: the one is on how skillful operational strategies organize the robotic behaviors to make the necessary but hidden information externalized onto the display; and the other is on how different operational strategies exhibit different manners of practicing the search procedures.

Chapter 5 provides a formal approach to designing human-machine interaction channels between a human operator and a machine autonomy. The essential differences in physical and cognitive capabilities between humans and machines can contribute to providing different accesses to an identical task situation, and so can enhance the total system performance. Composing "mixed-initiative interaction" between human and machine agents, in which their roles and initiatives are not fixed in advance and appropriately assigned depending on the situations, has large potentials toward the truly effective human-machine collaboration. However, any interventions by other than his/her own decisions may be the factors to disorder human control. They could hurt the system's operationality from the operator's perspective by introducing unexpected behaviors into the system. Concerning this issue, a shared-control environment composed of a human operator and a autonomous mobile robot is investigated based upon the classification of information types defined in Kirlik's *Generalized Lens Model* framework. After this analysis, a new human-robot collaboration style with the *shared communicational modality* between the human operators and the robot autonomy is proposed. This model of human-robot interaction is implemented into an actual tele-operation environment, and then evaluated in terms of the mutual relationship of the cue-utilization strategies between the two as well as their joint task performances.

Chapter 6 addresses the adaptability in the human-machine collaboration as a necessary element for the adequate coordination between human and mechanized control. Currently, all efforts to resolve any mismatch between humans and machines are charged only to the human operators as machines have no ability to deal with and adapt to variable behaviors of their human partners. Concerning this issue, inspired by our human proactive actions to the external world, the author advocates introducing proactive agency into the machine autonomy so that it can probe or sound out the partner's *covert* judgments for its adaptation. This behavioral model is implemented into a simulated shared-control environment, in which both a human operator and a machine autonomy can control the behavior of a mobile robot. Using this testbed environment, this chapter investigates their joint activity and then discusses feasibility of the *co*-adaptive approach towards the well-coordinated collaboration by the human operator and the machine autonomy.

Finally, Chapter 7 summarizes several contributions of this dissertation.

Chapter 2

Concept of Co-Adaptive Human-Machine Interface

"If a system's one-on-one interaction with its human user is not pleasant and facile, the resulting deficiency will poison the performance of the entire system, however fine that system might be in its other aspects." Jef Raskin [35]

2.1 Basic Approach of Co-Adaptive Systems Design

Any computations in a mechanical system are on the basis of symbol processing *closed* inside the system. In order to apply such closed symbolic systems to the actual problems, the system needs something to mediate the adequate correspondence between its internal symbols and the actual affairs in the work domain (i.e., to "ground" the symbols onto the actual). Machine autonomies to date, however, have handed this mandatory function to humans, either designers or users. The machines themselves make no contribution to it. Thus, the manners in which the machines are involved with the external world are static while they are performing their tasks. This static coupling will go into collapse as the decision structure of the machine autonomies become more complex. Designers cannot fully understand all the possible ways the machines can behave. Users cannot properly understand, supervise and interact with the automated systems. This is a key problem within "single-minded" machines.

The author approaches to this issue from the perspective of *co-evolutionary* human-machine systems [16] by introducing a new concept of "co-adaptive" interface that facilitates mutual adaptation processes between humans and machines. This chapter presents some basic ideas for this concept, each of which is summarized as follows:

- The height of human-machine collaboration is the point at that the machine

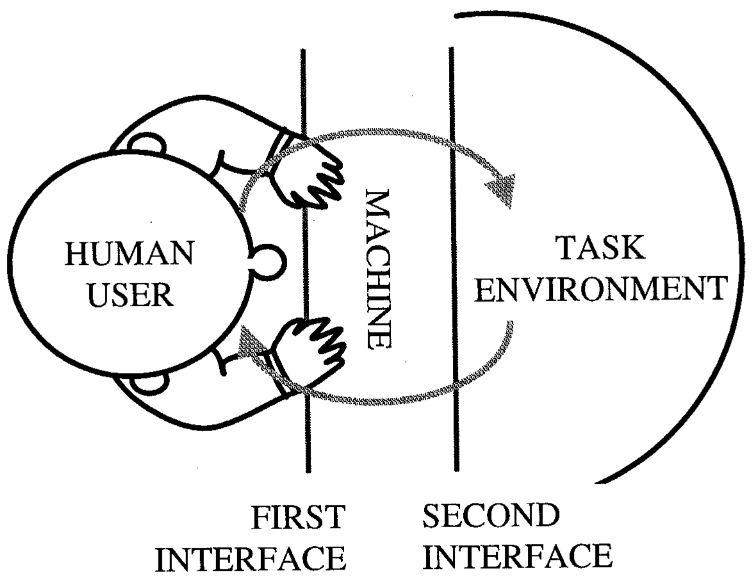


Figure 2.1: Dual interfaces when a machine mediates the interaction between a human user and its task environment

becomes *transparent* in its user's consciousness; the machine becomes integrated as the user's extended body.

- Unavoidably, though, deviations from such a well-coordinated relationship between the machine and the user will sometimes appear, however deliberately the system is designed. Recovery and outgrow from this bottom require the "conversations" towards the agreement between the two entities. Although something competitive and conflictive between them will arise in the process, such an ideal state of collaboration is always formed and reformed through experiencing the conflicts and by introspecting the competitions.

- Good human-machine interfaces should provide some bilateral information channels, through which both humans and machines can exchange their exploratory acts to adjust their judgments to each other. Dynamic interactions through those bilateral information channels would shape the flexible or ever-changing collaboration with adequate mutual dependency and reciprocity between a machine and its user.

2.2 Height of Human-Machine Collaboration

When a human user interacts with its objective environment mediated by an artifact or mechanical instrument, there should exist *dual* interfaces between them as shown in Figure 2.1 [40,41]. The *first interface* represents the human-machine interface,

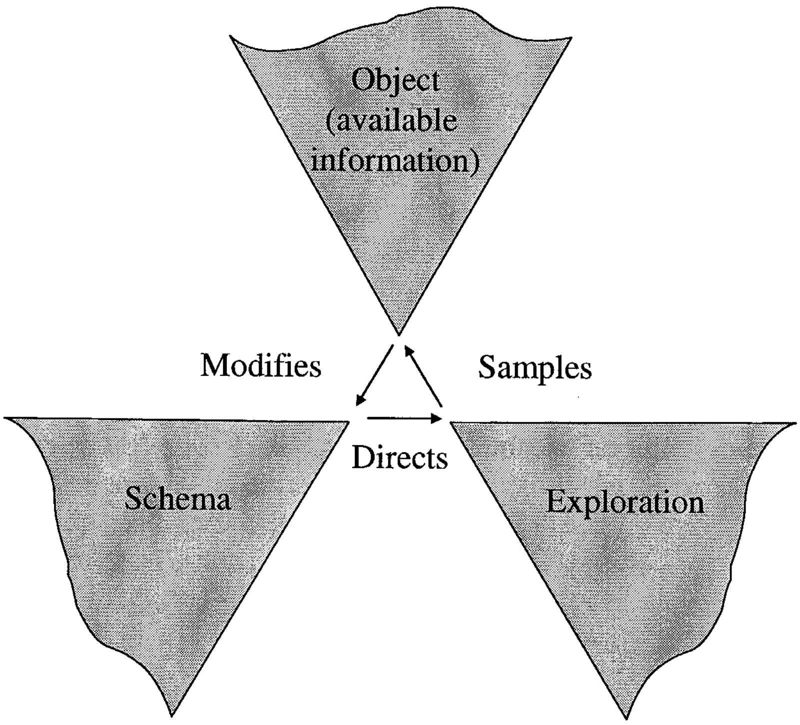


Figure 2.2: Neisser's view of the perceptual cycle (from [31])

literally located between the human operator and the machine. The *second interface* represents the machine-environment interface, through which the machine interacts with the environment. This distinction of the interfaces can be associated with the *proximal versus distal* distinction in human perception deployed in Brunswik's psychological modeling framework [4, 6, 15] (see Appendix A.1).

When the user can make full use of the machine on his own, these two interfaces get "unified" in his consciousness. As the philosopher Polanyi [34] noted, prior to full achievement of a skill, the performer's awareness focuses on the components of the skill. But, as the skill develops, the performer eventually develops a "focal awareness" of the distal as "subsidiary awareness" of the mediating chain (i.e., the components of the skill) subsides to the point that the chain becomes *transparent*. From this point of view, the unified interface is equivalent to this "transparentized" chain, which constitutes of the user's "extended body" and can create the phenomenological feeling in him as if he is directly manipulating the objects in the distance. At this stage, the user has developed his mental models as isomorphic to the behaviors of the integral human-machine system in the distal domain. Therefore, he can adequately anticipate or think ahead the resulting interaction of the system with its environment.

This state of elegant human-machine collaboration can be also explained in terms of Neisser's theory on human cognition, i.e., his view of the *perceptual* *cycle* [31] (Figure 2.2). He argued that knowledge in the form of schemata (or mental models) leads to anticipation of certain kinds of information. As such, the observer's active schemata mentally structure the flow of events; they effectively direct exploratory movements, and increase receptivity to particular aspects and interpretations of the available information. Meanwhile, as the data that the observer samples or picks up from the environment are absorbed by the schema, they serve in turn to modify or update the information and events that the schema is prepared to receive next. Continuous wheeling of this exploratory cycle represents that the observer's smooth interaction with the environment is achieved.

In the human-machine collaboration, this cycle is completed by the *isomorphism* [19] between the behaviors of the system and the user's mental models on them. The principle of Vicente and Rasmussen's *ecological interface design* [52, 54, 55], the goal of which is to make the intermediary computer as transparent as possible, can be regarded as artificially embedding the similar type of isomorphism into the displays, thereby providing the effective interface designs coherent with the ways of human thinking and perceiving performed.

2.3 Exploratory Interaction toward Agreement

The height of human-machine collaboration, at which human users spontaneously perform their tasks with machines, can be represented by the state that they are attributing themselves to distal events, conscious neither of complexity nor difficulty to handle the intermediary artifacts *per se*. Unavoidably, though, deviations from such a well-coordinated human-machine relationship will sometimes appear, however deliberately the system is designed. It is especially true in the case that the machine has high degree of "autonomy" [2] free from intervention by the human user, which means the increasing complexity of the system.

The essential differences in physical and cognitive capabilities between humans and machines can enable promising combinations of their individual decisions complementarily, in which those differences will give different accesses to an identical task situation that can enhance the entire system's performance. At the same time, any interventions by other than his own decisions may be the factors disordering the user's control. They could hurt operationality of the system from the user's perspective by introducing unexpected behaviors, thereby breaking the isomorphism for the smooth interaction: the machine eventually absorbs his focal awareness because he cannot anticipate its behavior accurately and needs intimate feedbacks for handling; and, the second interface gets "far away" from his proximity in the psychological sense.

These sorts of experiences will make us feel that the machine seem to act as if it has a mind of its own. Thus, we can say that machines have the *dualism* in the relation to their users: they behave as the instruments at one time, and do as the

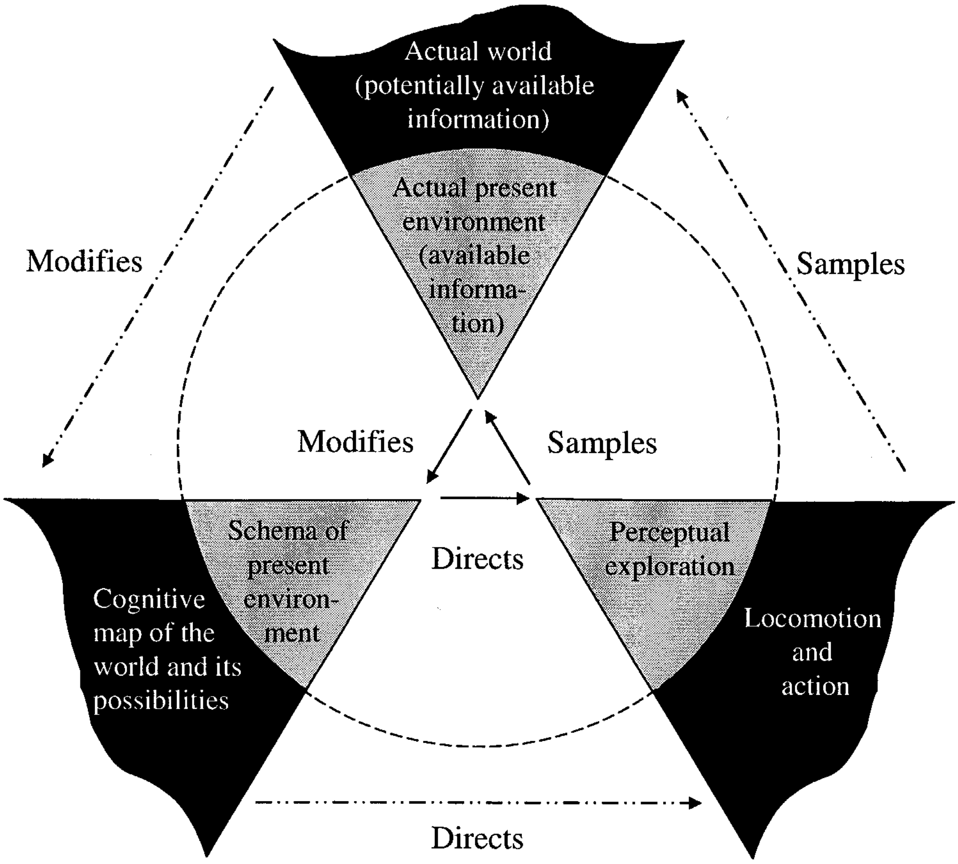


Figure 2.3: Expanded view of the perceptual cycle (from [31])

collaboration partners at another. However, all efforts to resolve any competitions and conflictions between humans and machines are charged only to the human users (i.e., to human adaptation). The machine autonomies basically execute what they are programmed to do close-mindedly, and so have no ability to meet and adapt to their partners. Recovery and outgrow from this bottom require "conversations" towards the agreement. Then, the role of human-machine interaction design is to give automated systems the *sociality* with their users. This social interaction explores the plausible relations where the respective contributors find their ways to commit to the joint activity, developing a common understanding of their task ecology.

Return to Neisser's framework. The exploratory processes in the observer will sometimes uncover data that the schema does not expect, or they will fail to find data that it does expect. To handle these sorts of circumstances, he expanded the view of the perceptual cycle as shown in Figure 2.3. In this expanded view, the inner circle is the perceptual cycle aforementioned while the outer circle is a more general exploratory cycle. The latter cycle includes actions taken to obtain information that is not present in the immediate environment. This exploratory or knowledge-granting actions are named *epistemic actions* [26, 28, 29], distinguished from *pragmatic* or performatory actions. They are physical actions along with pragmatic actions, but their primary function is to improve cognition. They play an important part in our human flexible and skillful performances in the complex real world as they make up an efficient strategy to reduce our cognitive burden such as inferring some indepth structures in the work domain. Kirlik has conceptualized the role of epistemic actions as "the exploitation of latent constraint in the behavior of the human-environment system which causes overt, perceptual variable values to covary with, and thus carry information about, the values of covert environmental variables" [26].

In order to develop a common understanding of the situations in their task ecology, each agent (human or mechanical) should adequately be aware of what their partners are doing and going to do, which will in turn construct their next situations. Exchanged acts toward this "team situation awareness" [37] among them are basically of epistemic actions. They seem to be superfluous elements on the surface, but they are actually critical in the collaboration. Therefore, collaborative human-machine systems must take into account and accommodate such interactions.

2.4 Mixed-Initiative Interaction Emerging through Co-Adaptive Interface System

The socially epistemic actions mentioned above configure the "mixed-initiative interaction" between humans and machines because these actions in their joint activity aim at a common understanding of the situations, thereby finding their own "niches" in their collaborative works. The term *mixed-initiative*, here, refers to "a flexible interaction strategy, where each agent can contribute to the task what it does best", and basically "the agent's roles are not determined in advance, but opportunistically negotiated between them as the problem is being solved" [1]. Although something competitive and conflictive between them will arise in the process, an ideal state of collaboration is always formed and reformed through experiencing the conflicts and by introspecting the competitions.

Machines should be evolvable in this sense. They should be tailored to people rather than expecting people to adapt to technology. They have potentials enough to influence human judgments and operations as they are intermediary processes which have accessibility to the first interface as well as the second interface. Then, good human-machine interfaces should provide some bilateral information channels, through which both humans and machines can exchange their exploratory acts to adjust their judgments to each other. The author defines such interface systems, which can facilitate their mutual adaptation processes, as the "co-adaptive" human-machine interfaces. Figure 2.4 illustrates this basic concept. Dynamic interactions

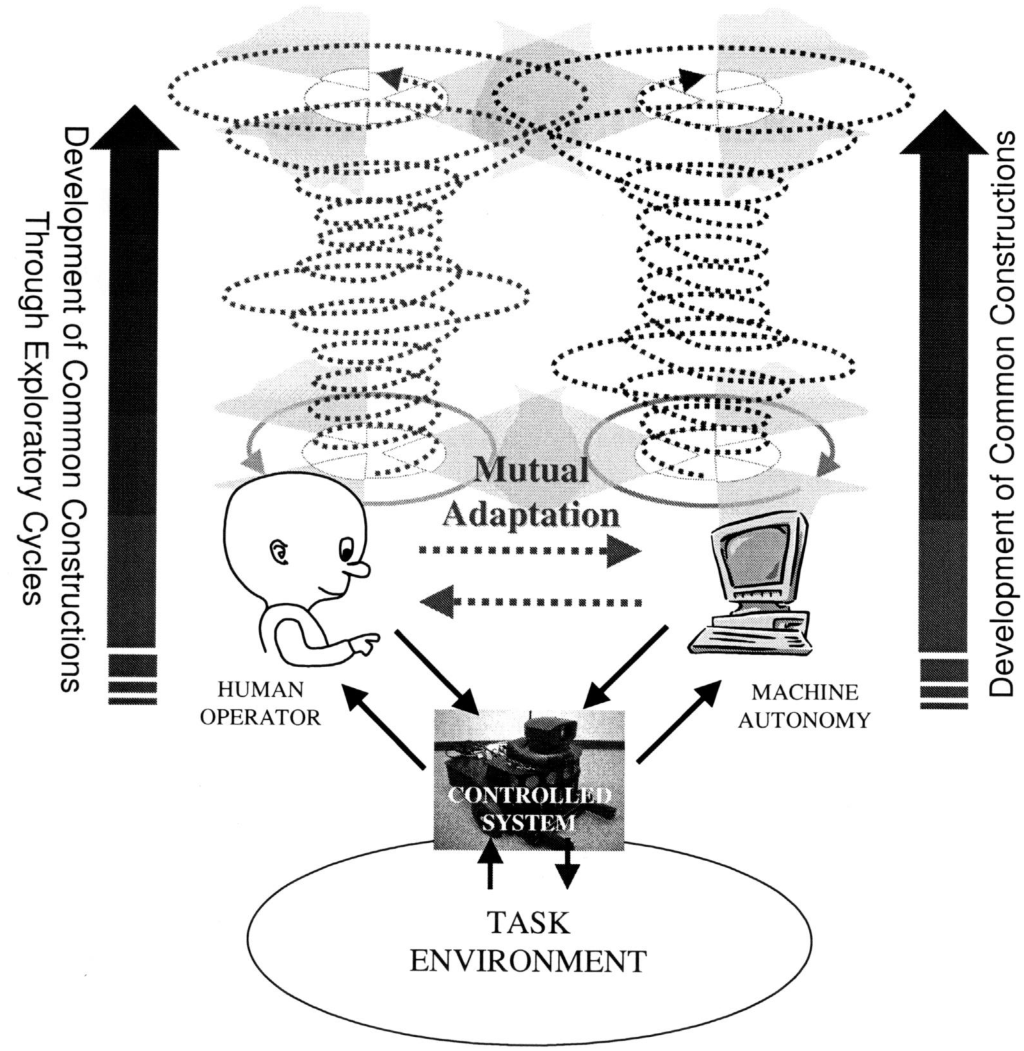


Figure 2.4: Reciprocal exploratory acts shaping common constructions through bilateral information flows

of their reciprocal exploratory acts through those bilateral information channels will shape the flexible or ever-changing collaboration with adequate mutual dependency and reciprocity between a machine and its user. A "one-on-one" relationship between the system and the user is expected to emerge from such interactions driven by their exploratory cycles.

Chapter 3

Analysis of Behavioral Task Structures for Tele-operation Environment

3.1 Introduction

In every tele-operation environment, there exist some intermediary computational processes between a human operator and the end effectors, all of which constitute one large and complex artifact tool that works as the bridge between his/her manipulations and the actual system performances in the remote location. The ideal condition for the operators spontaneously and smoothly performing their tasks is represented by that they are attributing themselves to distal or remote events, conscious neither of complexity nor difficulty of the artifact manipulation *per se*. As the philosopher Polanyi [34] noted, prior to full achievement of a skill, the performer's awareness focuses on the components of the skill. As skill develops, the performer eventually develops a "focal awareness" of the distal as "subsidiary awareness" of the mediating chain subsides to the point that the chain becomes *transparent*[1]. From this perspective, the state in which the operator has to attend to the handling of the tool (i.e., the components of the skill) corresponds to his awkward performance, and will induce his increasing workloads as spending more cognitive resources in it. Hence, the desirable human-machine interface system facilitates such distal attribution, and creates the phenomenological feeling in the operators that they are "directly" monitoring and controlling the functions of the system [52] as mentioned in section 1.2.1.

In order to approach this issue, this chapter examines the feasibility of some kind of facilitating systems, which can mediate the interaction between a human operator

[1]In terms of this Polanyi's insights on skill acquisition, Loomis has discussed the phenomenon of "distal attribution" in tele-operation environment (see [30]).

and a teleoperator robot, and that can extend the operator's actual perception-action cycles to the *quasi*-direct perception-action cycles in the ideal tele-operation environment with the operator's distal attribution established. At first introduced is a new concept of "intertask morphology" as the *isomorphism* [19] between two different tasks. Based on this idea, here presents some careful analyses to find out the invariant structures that are common between two different behavioral tasks in a tele-operation environment.

The testbed tele-operation environment is developed with virtual reality authoring devices and an actual mobile robot so as to embody a different way of human operation than the usual like the one by joysticks. The feasibility of the behavioral mapping is examined, by which a human operator can control the robot to "catch a coming ball with its body" while using his/her behavioral skill of "hitting a coming ball into the target area with his/her hand".

These two tasks are analyzed into some qualitatively different phases. Thus, *Adaptive Resonance Theory* (ART) [5, 14, 17] neural network model is deployed to detect the boundaries of those phases during the operator's performing tasks in real time. The effects of the time-delay and the discontinuity in displaying the feedback information about an operator's skill performance within a VR space are also discussed. They may prevent an operator from naturally exerting their behavioral skills. The author addresses this problem by deforming objects in the VR space corresponding to the abstract behavioral phases derived from the ART model, which has learned the operator's motion properties.

3.2 Intertask Morphology Bridging Different Behavioral Tasks

Rasmussen [36] has proposed that there exist three different cognition levels concerning with the operator's behavioral modeling; SBB (skill-based behavior), RBB (rule-based behavior) and KBB (knowledge-based behavior). SBB is a behavior in which the specific features are experienced together frequently and the response is more or less automatic, while RBB is a procedural-oriented task including monitoring and interpreting. KBB includes the full range of problem solving and planning activity with the manipulation of some kinds of "deep" models. This is illustrated in Figure 3.1. In the light of this behavioral trinity model, the human-machine interactions sustained by SBBs are the ideal, meaning that the intermediaries would become *transparent*.

By nature, however, human operators in tele-operation systems confront with considerable difficulties in recognizing the actual situation around the robot because of their impoverished perceptual conditions on the remote site. The distal situation should be "reconstructed" or judged from the transmitted raw data that

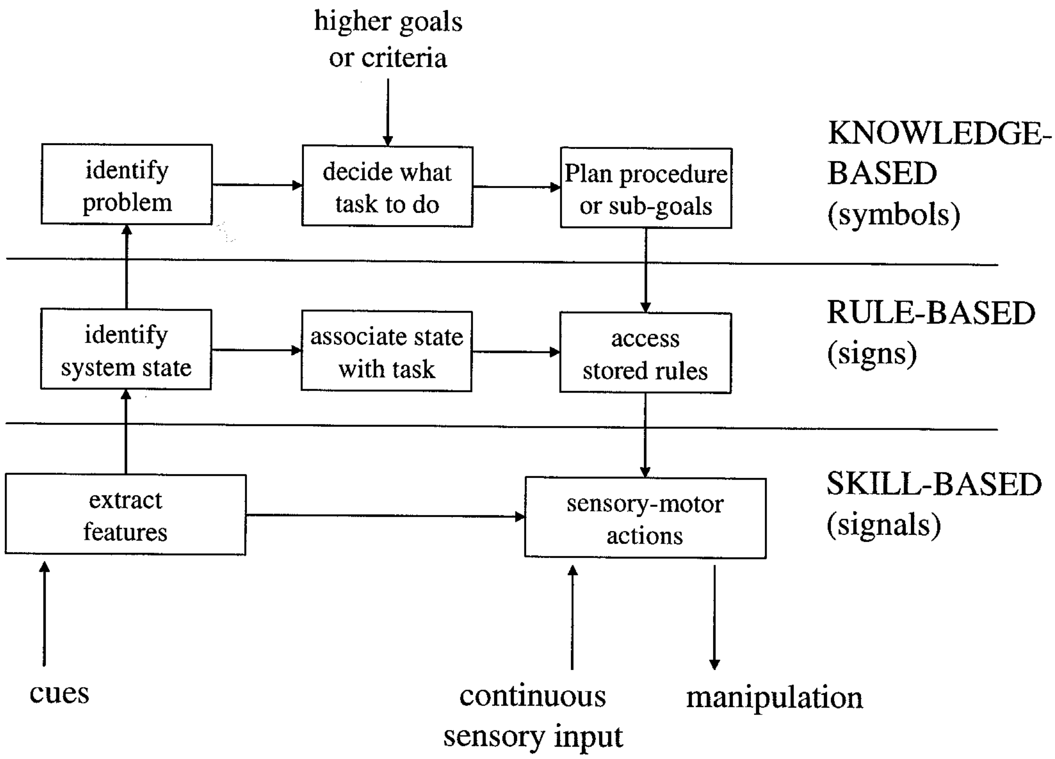


Figure 3.1: Rasmussen's SRK model

are shown in the display. The important characteristic of SBB for distinguishing it from RBB and KBB is its behavioral "continuity", which takes the form of a chain of reactive "perception-acting" units, and therefore it enables proficient, skillful interaction with the environment. Thus, some kind of mediating systems would be desirable, which can extend the operator's possible perception-action cycles to the direct perception-action cycles in the ideal tele-operation environment as shown in Figure 3.2.

Toward this interaction aid, we need to find out some correspondence relations between manipulation acts by the human operator and behavioral acts by the tele-operator. This work is comparable to the *ecological task analysis* [25], which should be done first in Vicente and Rasmussen's *ecological interface design* (or EID) framework [54]. In EID, the inherent task structure revealed by the careful task analysis is mapped onto the geometry of the display components in a way that exploits direct perception (i.e., to "make visible the invisible"). By enabling the operators to directly act on the display representing the inherent task structure, EID supports human interaction with the system via the perception-action cycles, instead of the chain of inferences to compensate for the decrease in information availability that demands the operators' conscious efforts so far. By supporting interaction

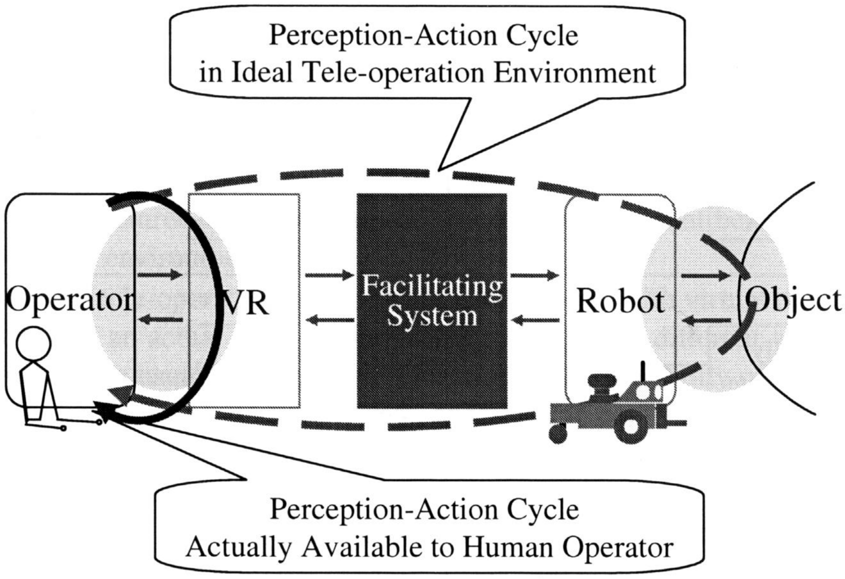


Figure 3.2: Ideal and actual perception-action cycles of the human operator

via the intrinsic perception-action cycle, EID can reduce the operator's deliberative reasoning burden, and also can provide appropriate computer support for more cognitively laborious processes. We should, however, note that this approach is effective only to the tasks, whose structures are temporally invariant, and therefore which can be achieved by "moment-to-moment" judgments. But it cannot deal with the tasks which may change their semantics along with the operational context.

In order to approach this issue, the author introduces a new concept of "intertask morphology" as the *isomorphism* [19] between two different tasks. Isomorphism is, here, a mathematical concept which represents "a one-to-one correspondence between the elements of two sets such that the result of an operation on elements of one set corresponds to the result of the analogous operation on their images in the other set". To realize the ideal perception-action cycle between the human operator and the robot shown in Figure 3.2, the facilitating system should bridge the gap of their behavioral differences derived from their different perceptional and actional capabilities. Although human behavioral features are never identical with the mechanical, it would be possible to find out some invariant properties of task structures, i.e., morphology of task structures, at some abstract or conceptual levels. That is the key for this type of bridging.

3.3 Analysis of Task within Virtual Reality Space

In this section, human motion data captured from the experiment within a VR space are analyzed, in which a human subject performs a simple behavioral task; making

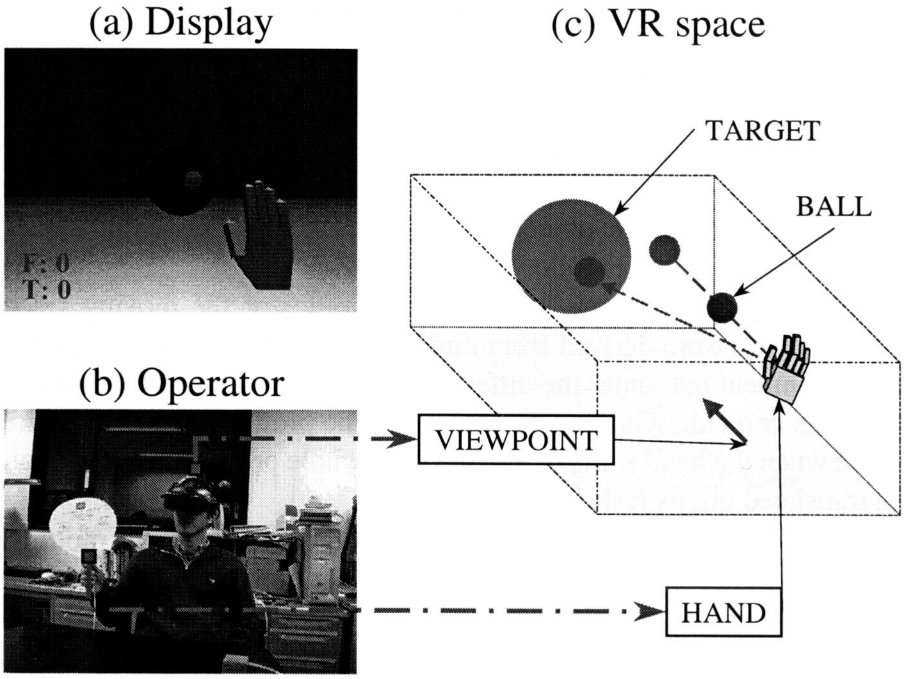


Figure 3.3: Experimental settings within VR space

a moving ball, which comes bound for him/her with a constant velocity, bounce into the target area by hitting it with his/her virtual hand.

3.3.1 Experimental Settings

Figure 3.3 shows the experimental settings here. The VR space is displayed to the operator through a head mounted display (HMD), in which appearance of the ball and part of the operator's body (i.e., a right hand) are displayed from his/her viewpoint. With the magnetic 3D position sensors (i.e., POLHEMUS 3SPACE FASTRAK SYSTEM) mounted on the HMD as well as on the operator's right hand, their movements are mapped onto the changes of the viewpoint and of the hand's positions in the VR space. Thus, the operator can dynamically interact with the space "through" his/her body motions. In this experiment, varying the velocity of the moving ball v_b from 20 to 40 units/sec does produce three different time constraints that bind the operator's reaction time allowed after he/she detects the ball. In each trial, an initial position and a moving direction of the ball, a pair of which is referred as a *trial environment* hereafter, are randomly changed based on a randomly provided seed value. Therefore, if the seed value is same, the same trial environment will be realized.

3.3.2 Invariant Structures of VR Space Task

Due to the different experimental conditions in terms of task time constraints and trial environments, trajectories of the hand motions of hitting a coming ball do differ in each trial. However, if we could change our perspectives from *external* observer's to *internal* actor's, some "common properties" will be detected with respect to how the actor interacts with the object in the task space. They are explicated by translating raw interacting data as follows.

On the one hand, Figure 3.4(a) shows profiles of the moving velocity of the hand, or v_h, that were derived from three different trial runs performed in the same trial environment but under the different velocity conditions of the ball. Where, the time points coincide with one another of all the profiles, and $t = 0$ corresponds to the time when the hand starts to move. Other whole profile data of the hand motions were translated in this fashion.

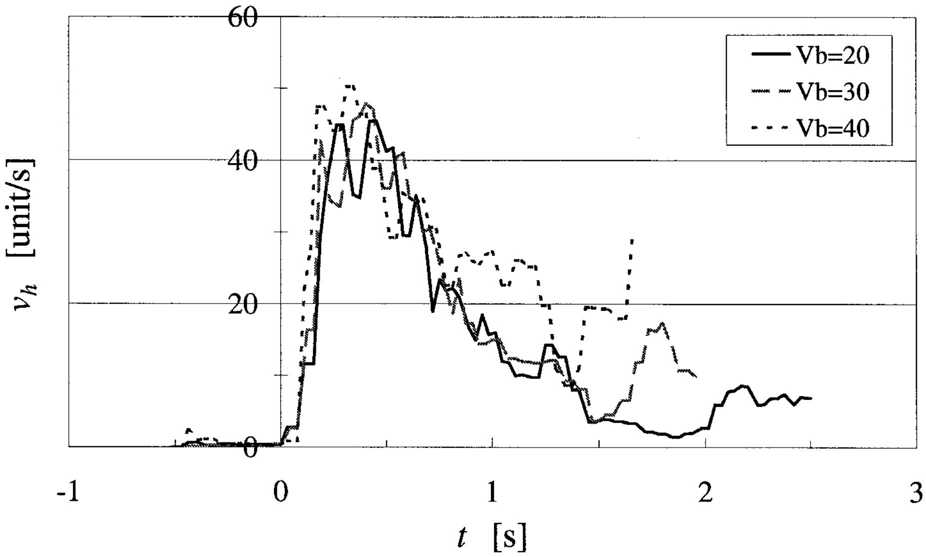
On the other hand, Figure 3.4(b) shows another translation by plotting a variable of $v_h/d_{l_{max}}$ for twelve trials, each of which has a different environment to the others in terms of both the initial position and moving direction of the ball. Wherein, $d_{l_{max}}$ is introduced for normalizing the differences in the distances the hand moved among trial environments, which denotes the maximum distance between a ball's linear trajectory and a hand's position. These figures show that, even with such a simple linear transformation, the interacting profiles of the hand revealed some common or invariant structures, i.e., an *intratask morphology*.

Based upon these translations of raw motion profile data, this behavioral task was analyzed into the following four qualitatively different phases:

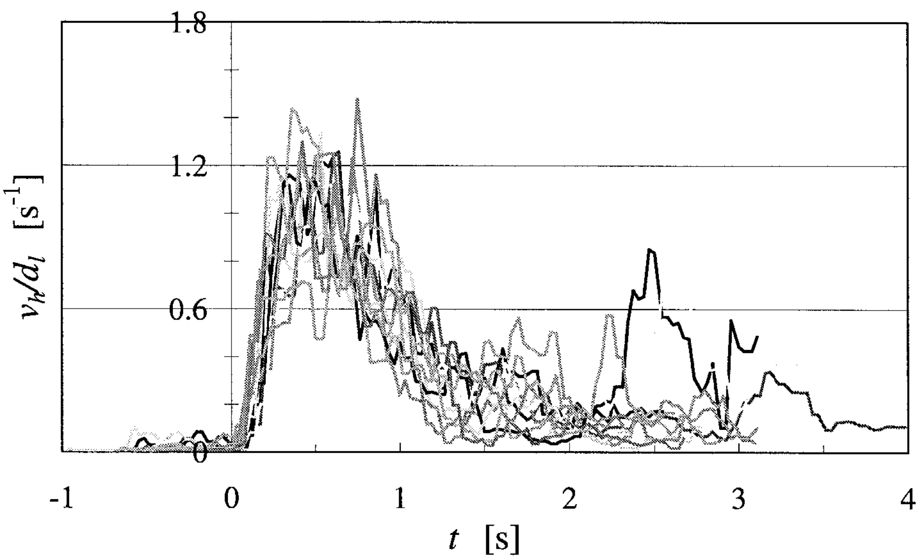
1. In **Phase A**, the hand is not moving at all just after the coming ball is identified so as to predict the ball's trajectory.

2. In **Phase B**, an actor accelerates his hand toward the predicted impact point. Notice that the profiles of v_h in this phase are almost the same (i.e., with the constant acceleration) despite the differences of a ball's velocities and relative positions of a hand against a ball. Figure 3.5 shows all the slopes of v_h, indicating their similar constant acceleration of the hand. This demonstrates that some kind of "feed-forward" process initiated by the prediction in the former phase is ongoing within the actor, rather than based upon the feedback information.

3. In **Phase C**, the actor's hand-positioning task is dominant. By decelerating a hand's movement, the actor attempts to place a hand exactly to the final impact position. Adjustment of the velocity herein is dependent upon the temporal observation of a ball and of the actor's hand, thus a visual feedback process is ongoing.

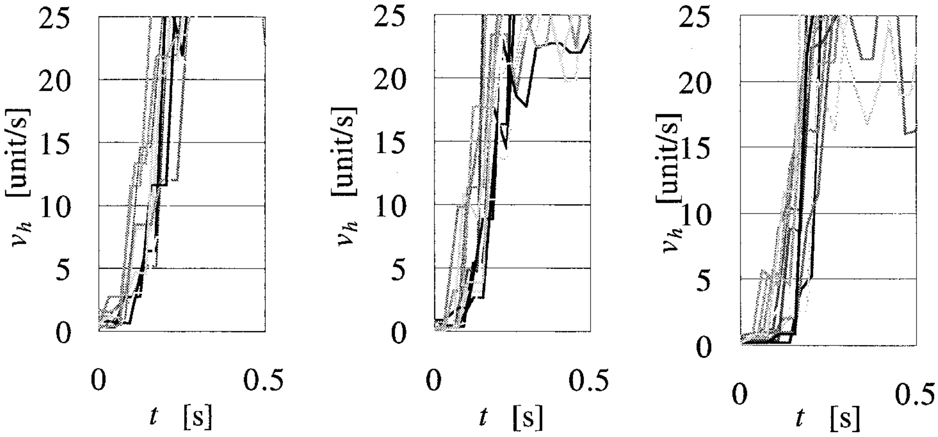


(a) Profiles of v_h with three different v_b settings



(b) Profiles of v_h/d_l in twelve different trial environments with $v_b = 20$

Figure 3.4: Comparisons of profiles of the hand's motions in different trial environments



(a) $v_b = 20$ (b) $v_b = 30$ (c) $v_b = 40$

Figure 3.5: Profiles of v_h in phase B

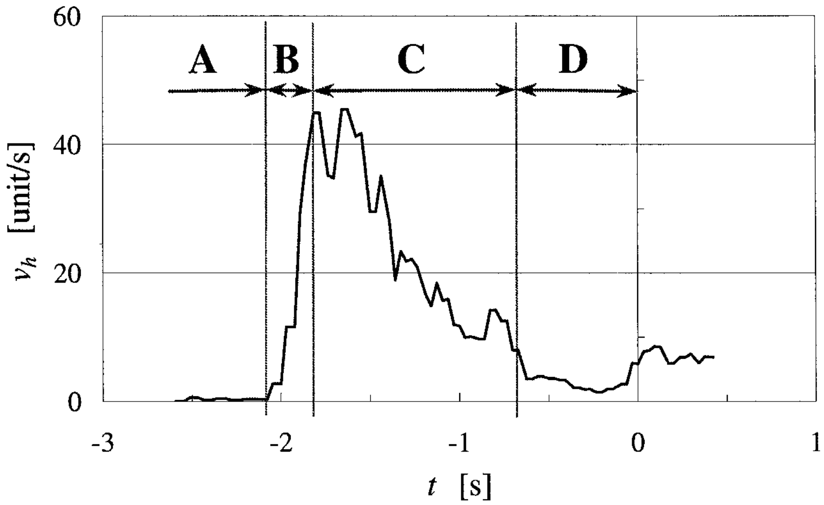
4. In **Phase D**, a hand impacts with the ball. As in Phase A, the hand does not move any more and the moment of impact is carefully pursued.

The typical motion consisting of these four phases is shown in Figure 3.6, in which a profile of a hand velocity v_h is shown in (a) and relative positions of individual phases are illustrated in (b).

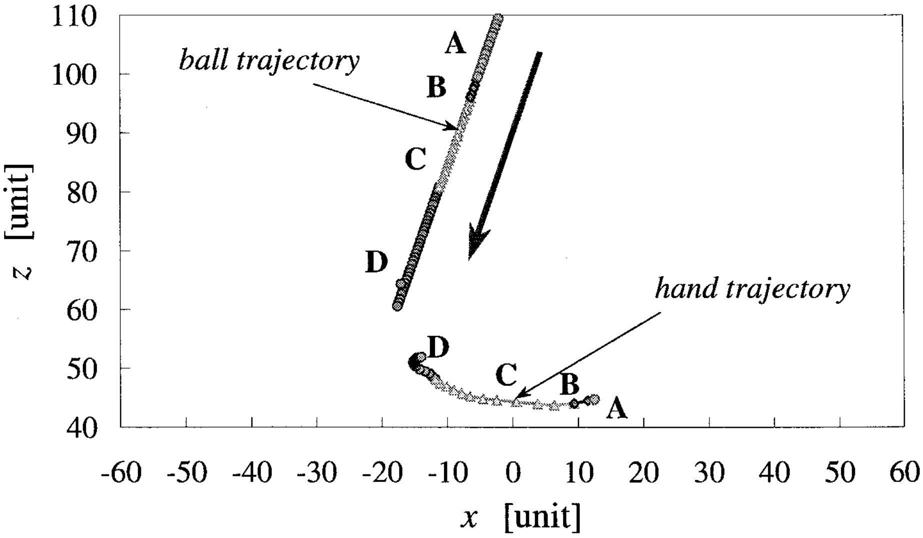
The foregoing observed task structure consisting of Phase B and C is consistent with Schmidt's *motor schema* theory [23, 42, 46]. In this theory, he distinguished between a *recall schema* and a *recognition schema*, both of which make up a human motion memory. The former is responsible for the feedforward process of the proficient skilled motion, while the latter is responsible for the feedback process. He stressed that some relations among the motion intents, situational specifications and motion commands are preserved at the abstracted level in the motion memory as a recall schema, while relations among the motion commands and the expected sensory consequences are preserved as a recognition schema.

3.4 Automated Recognition of Behavioral Task Structure

This section attempts to automate the recognition of the motion structure in the behavioral task analyzed in the former section. That is, the human actor's motion sequences are segmented into the groups corresponding to the four different phases clarified in section 3.3. To detect boundaries of the distinguished phases from a



(a) Data profile of v_h (t = 0 indicates the moment of the impact)



(b) Motion trajectories of the ball and the hand from the top view, where individual task phases are coded in different colors

Figure 3.6: Four qualitatively different phases composing the behavioral task in the VR space

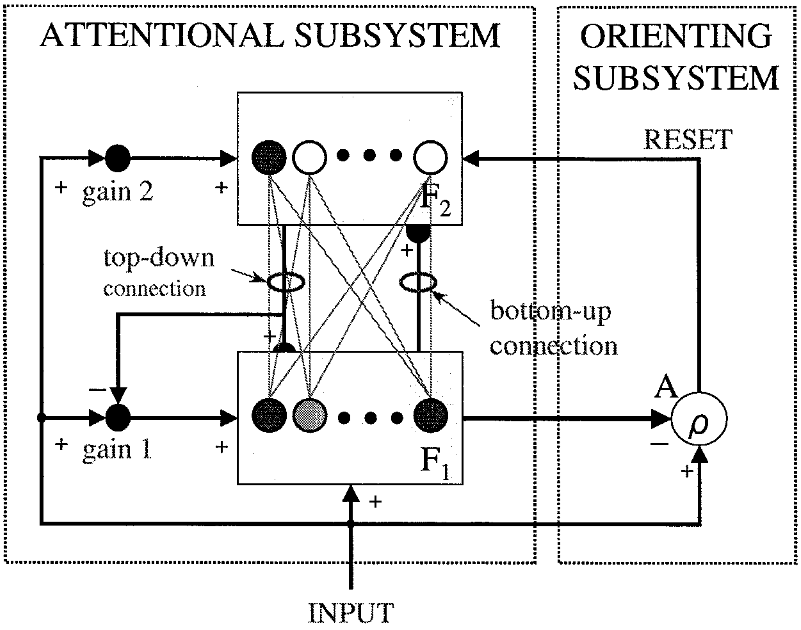


Figure 3.7: Block diagram of the ART model

continuous stream of motion data which may of course contain noises, the Adaptive Resonance Theory (ART) model [5, 14, 17] is employed.

3.4.1 Architecture of ART Model

Figure 3.7 shows the architecture of the ART model. This artificial neural network is referable to a computational model which can learn pattern recognition in an unsupervised fashion. It can organize input patterns into clusters at a variety of abstraction levels by varying its internal parameter, called the *vigilance* parameter.

Within the ART model, prototypes for each of clusters, which are memorized in the connections between two different neuron layers (denoted as F_1 and F_2 in the diagram), are constructed and reconstructed dynamically. Those prototypes play a key role in the subsequent classification in a sense that they will function as a kind of bias in interpreting other coming streams of data. Which cluster a new input pattern will be assigned to is determined by calculating the similarities of the data with the respective existing prototypes. The vigilance parameter ρ, whose value is set between $[0, 1.0]$, determines a common acceptable condition of data classification. When the value of a vigilance parameter is large, the classification would be less affected by what it has learned so far (i.e., prototypes) and the model tends to generate more distinctive and competitive categories. Conversely, with a smaller value, the ART model becomes a more conservative classifier, affected more by the prototypes and assimilating new data with the previously existing memory. In this case

ART generates more abstracted, coarse categories than the former does. Therefore, the ART model functions as an unsupervised dynamic classifier that can generate multigranular categories with a simple adjustment of the vigilance parameter.

3.4.2 Recognizing Task Structure Using ART Model

Using the ART model, a series of behavioral motions is classified into the abstract operational phases. Input vectors to the model are time-series of snapshot data collected while a human actor interacts with the VR space. They consist of the following variables;

i_1: Velocity of hand movement ($v_h/d_{l_{max}}$)

i_2: Acceleration of hand movement

i_3: Distance between the trajectory of the ball and the hand

i_4: Distance between the ball and the hand in the actor's view

i_5: Visible size of the ball (i.e., appearance of the ball)

Where, the first two variables (i_1 and i_2) represent sort of the actor's *proprioceptive* sensory data, relating to stimuli arising within him/her, while the last two variables, i.e., i_4 and i_5 denote the *exteroceptive* sensory data, relating to stimuli received by the actor from outside. The third one represents the current status while the actor is interacting with the VR space. These data are normalized within the individual variables and make up a snapshot vector of the input data stream.

Figure 3.8 shows the resultant classification of an actor's motion sequence by the trained ART model. Herein the input data streams are overlaid by horizontal bold bars denoting the classified clusters (i.e., phases of the motion) along the temporal stream. This result is obtained by letting the ART self-organize its internal connections with the vigilance parameter set to 0.50. The result is actually reproducing the same form of phase transition as is observed in the former analysis of human motions (see also Figure 3.6). In this way, it seems to be possible to employ an ART model trained enough as an automatic detector to find plausible boundaries among the operational phases as human actors are performing tasks.

3.5 Deforming VR Space According to Operational Phases of The Task

Here is the discussion on the effects to the actor's skill performances of time-delay and discontinuity in the feedback information display about behaviors in the VR space. In addition, so as to deal with this problem, deforming representations of the VR objects corresponding to the operational task phases was attempted.

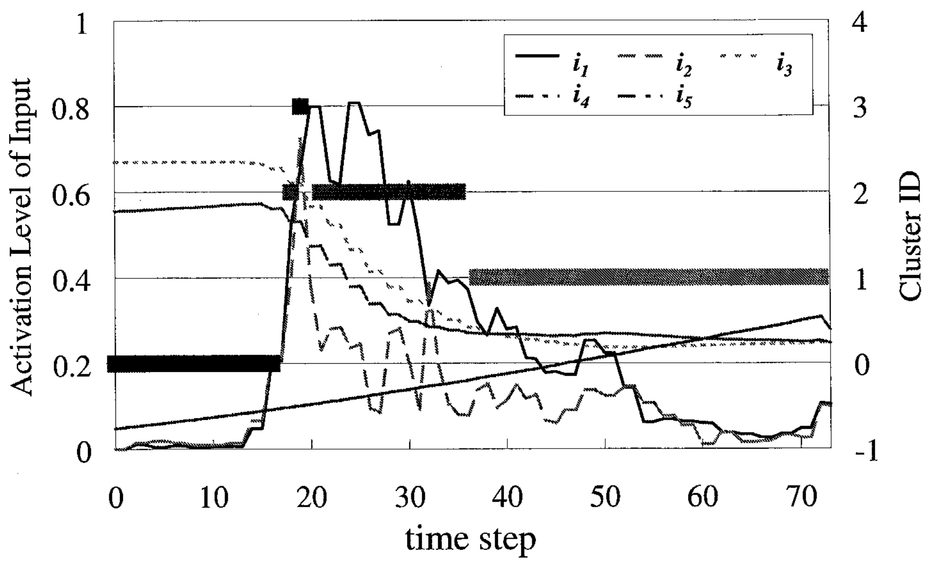


Figure 3.8: Segmented motion profile by the clusters derived from the ART model whose vigilance parameter was set to 0.50

3.5.1 Effects of Feedback Delay in Task Performance

The well-recognized technical problem of a VR-based tele-operation system is the delay and the discontinuity of the feedback information displayed resulting from communication and computational burdens. This problem drastically affects a human operator's operability and disables him/her from producing a naturalistic and innate response. The operator is further burdened because he/she has to reconstruct an expected actual reality from presented data. This is illustrated in Figure 3.9, which shows that an operator's perception-action cycle experienced within the VR space is quite different from the one experienced within the real world.

To the extent that an operator can control a robot's behavior in proximity and in real time without being intervened by VR, it would be easy for her to have an embodied cognition (i.e., a robot may become something like a part of her body). However, when a complex artifact intervenes, an operator needs some "aided eyes" that can bridge a gap between those different perception-action cycles.

To identify the effects of the time delay and the discontinuity of the feedback information, another VR task environment was developed in which the effects of the actor's hand motion is displayed in a variety of time delays. As shown in Figure 3.10, a simulated task environment was prepared where a constant delay of T_d is embedded in presenting the displays in the VR space of the appearances of the hand caused by moving the hand in the actual reality. The effects of the actor's movement (i.e., positions of the hand) are updated in display at intervals of T_d. The

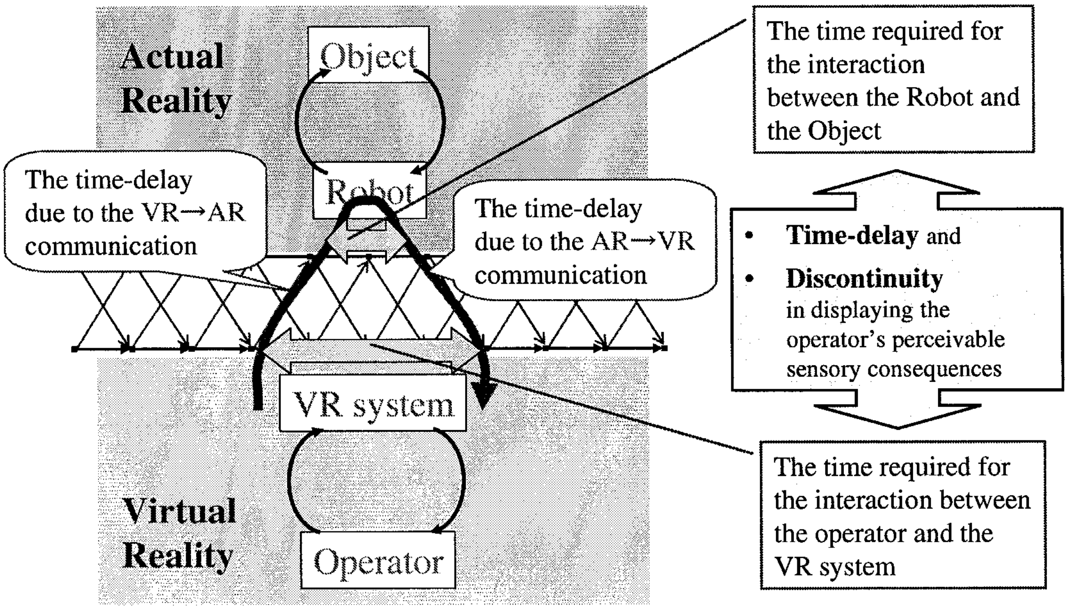


Figure 3.9: Delay for coupling two different realities

operator is forced to perform the task of hitting a coming ball with a racket under this environment.

Figure 3.11 shows the results of the experiments. In this figure, the degradation of task performance is observed as the delay increases, where the performance is measured by counting the number of successful trials (i.e., the hit ball bounces into the target correctly). This demonstrates that delays due to the intervention of the VR space in the tele-operation environment would do harm to the operator's skills and that thus some "aided eyes" are needed.

3.5.2 Aided Eyes for Operator

In order to make the task environment via the VR space more naturalistic to human operators, it was attempted to vary the ways of displaying information to the operator according to his/her ongoing task phases. More specifically, displays of the objects within the VR space are deformed in a particular way, based upon the characteristics of the human task performance analyzed in section 3.3.

As mentioned in subsection 3.3.2, during Phase C the operator much depends upon the feedback information. This means that the effects of the delayed display do harm to the task performance. Therefore, during this phase the transmission of the operator's hand movement to the actual reality is quitted, and a local feedback loop is constructed between the operator and the VR as illustrated in Figure 3.12(a). Detecting the hand starting to move, the system predicts and constructs the posture of the hand in the actual reality, which is presented to the operator in real time along

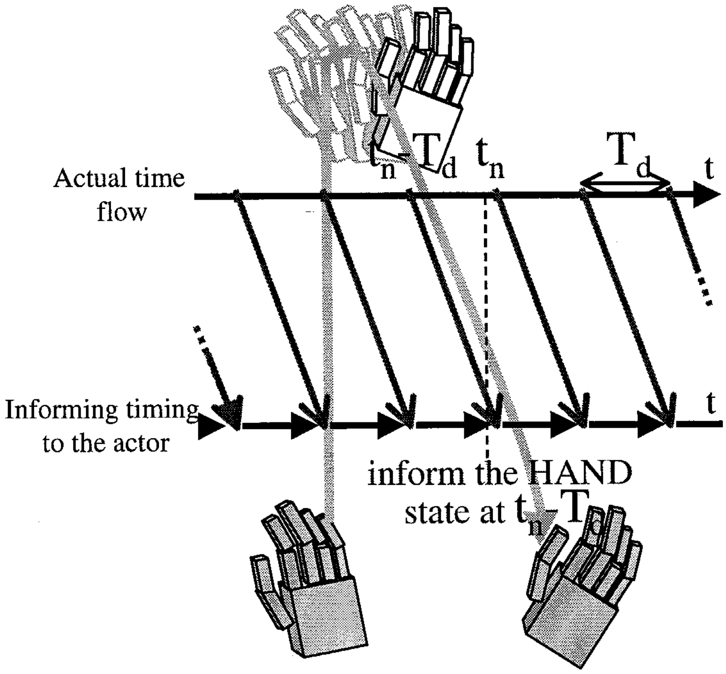


Figure 3.10: Simulating display information delay

with hand movements.

Conversely, a view of the target (in this case, a ball) is very sensitive to the operator's predicting the ball's trajectory during the feedforward-dominant process in Phase B, when the delay in displaying a ball to an operator makes him fail to hit it. Thus, a ball displayed in a VR is deformed from a globe to an ellipse whose longitudinal axis is matched with direction in which it is moving and its length is determined by the travel distance of the ball during the time interval distance of the ball during the time interval between display switching, as shown in Figure 3.12(b). Switching among the task phases is controlled according to real-time segmentation of a motion sequence enabled by the ART model, which has learned from a human-VR interaction series in an environment without any delay (i.e., $T_d = 0$) offline.

In this way, the proposed display system (Figure 3.13) both contributes to bridging the gap of the two different perception-action cycles having different time spans and evolves asynchronously. Figure 3.14 shows the results contributed by the method under the delay $T_d = 0.50$ sec and 1.0 sec as compared with performance of the task without any aided eyes. The figures denote that the method contributes to making an operator experience a naturalistic task environment even in a task environment where a large delay is inevitable.

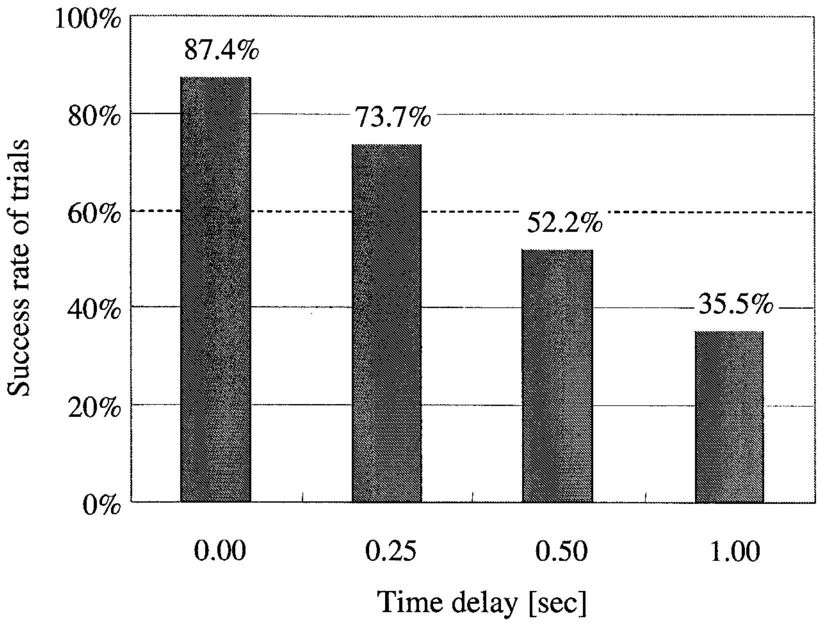
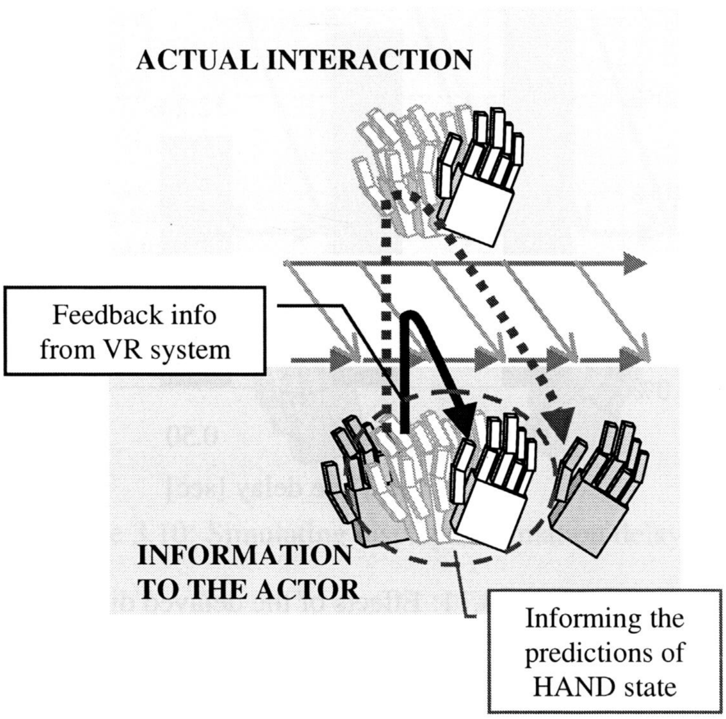


Figure 3.11: Effects of the delayed display

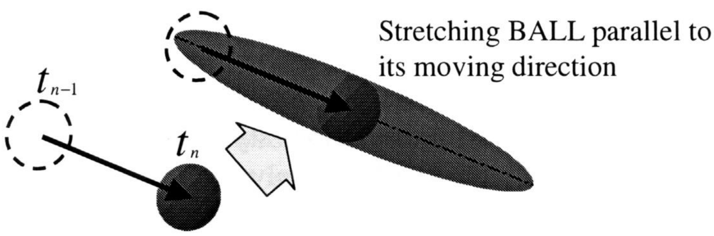
3.6 Toward Tele-operation System Based upon Inter-task Morphology

As shown in Figure 3.9, the delay discussed in the previous section is largely determined by the operational characteristics of the robot subsystem. Moreover, the operability of the tele-operation system as a whole depends greatly on the degrees of autonomy installed in the robot. Consequently, the interface for an operator must be flexible enough to catch up with the various styles of human-robot couplings [27]. At design time, it is impossible to exhaustively predict the specifications of the skill levels of human operators or the degrees of autonomy of machines; therefore, the ideal interface system for the tele-operation must consist of a number of *agents* or *facilitators*, each of which is able to self-organize the appropriate relationships with the others through interactions in a bottom-up, rather than top down, design. The status of such interactions among facilitators is directly or indirectly transmitted to human and robot perception-action loops, and individual perception-action cycles will be adjusted accordingly. This would be the idealized collaborative style with mutual evolution between the human and the machine.

Based upon the above discussion, the author attempted to develop the VR-based tele-operation system in which the operator and the robot are linked through some



(a) Interpolating the predicted hand position in Phase C



(b) The way to deform the ball

Figure 3.12: Deforming objects in the VR space

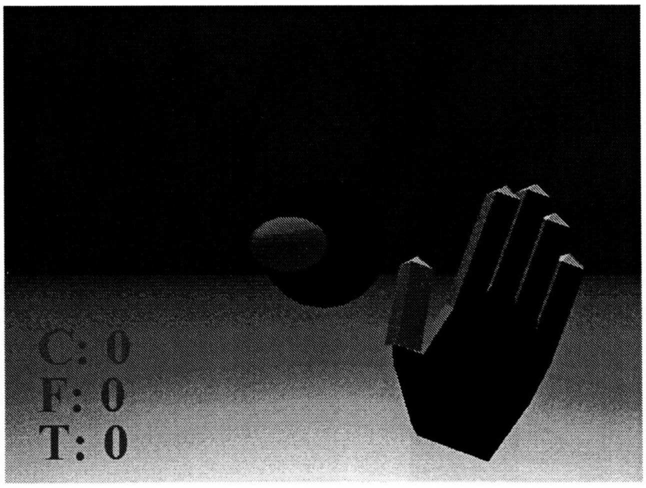


Figure 3.13: Screen shot of the deformed display proposed

intertask morphology. That is, using his/her behavioral skill of hitting a coming ball into the target area with his/her hand, the operator can control the robot's movements to catch a rolling ball with its body.

To analyze the structure of the robot's operating tasks, a tele-operation environment without the VR space is prepared as follows. The robot has visual sensors, ultrasonic range sensors and primitive actuators for forward and backward movements and steering. Yet another experiment was performed to see how well the proficient operator can control this robot by monitoring continuous visual sensor's live images transmitted to the operator in wireless UHF video signals and by commanding movement and steering instructions through a keyboard. Figure 3.15 shows an environment of this experiment. Figure 3.16 illustrates a data profile made by an operator's remote control performance. From this result, we can observe that a transition of four different phases does exist revealing a morphological task structure like the result shown in Figure 3.6. Although usable perceiving and actuating devices are completely different between those two tasks, they share a common task structure. This suggests that we would be able to design an ecological interface within which a human and robot facilitators interact with each other and form themselves reciprocally under boundary conditions of that common invariant task structure.

3.7 Summary

This chapter examined the feasibility of the facilitating systems which can mediate the interaction between the human operator and the teleoperator robot, by introducing a new concept of *intertask morphology*. This idea for human-machine interface

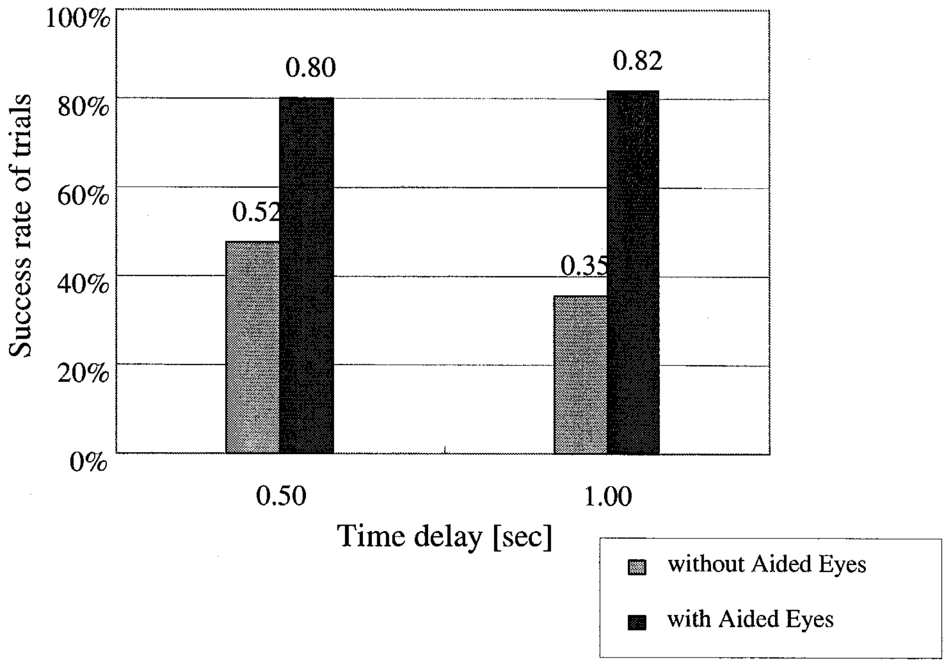


Figure 3.14: Improvements due to aided eyes

design aims at connecting two different behavioral tasks via their structural isomorphism, and extending the operator's actual perception-action cycles to the ideal perception-action cycles with his/her distal attribution established. From the perspective of intertask morphology, careful analyses have been done to find out the invariant structures that are common between two behavioral tasks in the VR-based tele-operation; the one task was configured in the VR space, in which a human subject hits a coming ball into the target area with his hand, while the other was done in the real world where a teleoperator mobile robot catches a coming ball with its body like a goalkeeper. These two tasks were analyzed as both decomposed into four qualitatively different phases, suggesting the potential of the behavioral mapping between them. The common form of the decomposition of these behavioral task structures was computerized by an ART neural network model. It can detect the boundaries of those phases during the human operator's performing tasks in real time. This computerization was exploited so as to cancel the effects of the time-delay and discontinuity in the VR-based tele-operation, by deforming objects in the VR space corresponding to the abstract behavioral phases derived from the ART model.

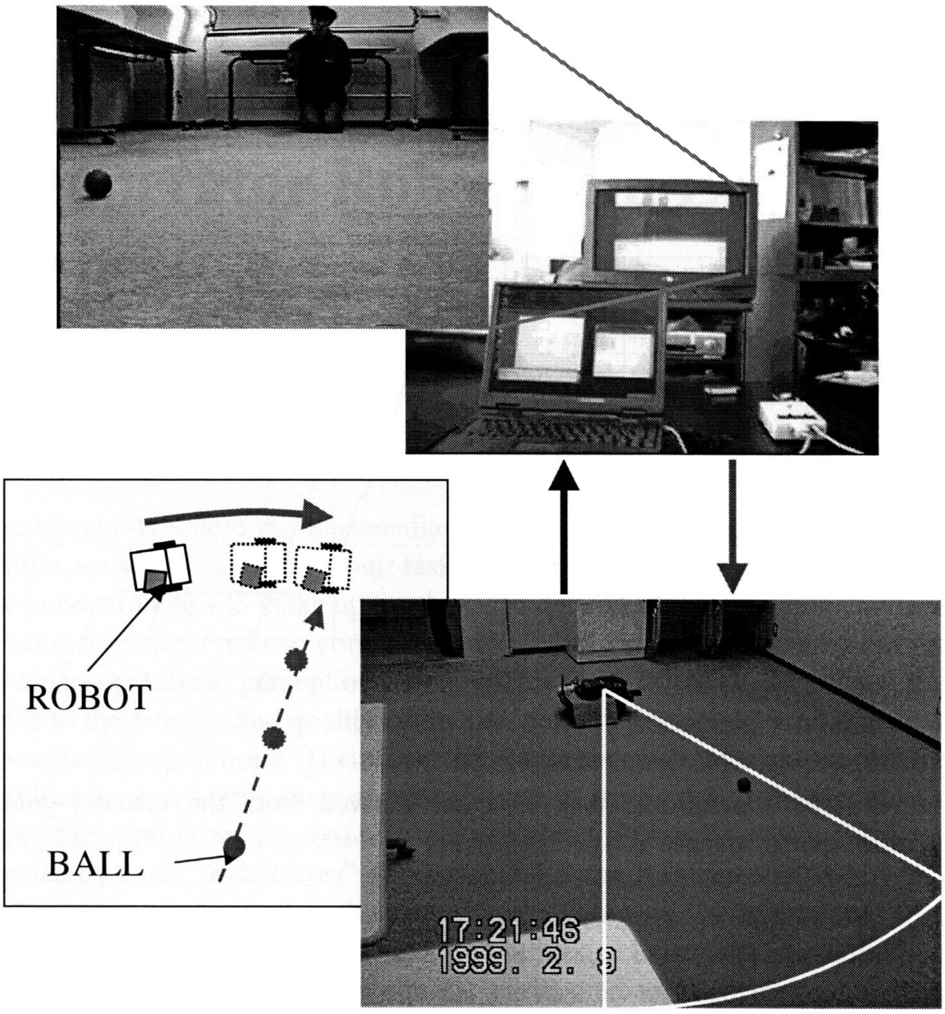


Figure 3.15: Developed visually-guided tele-operation system

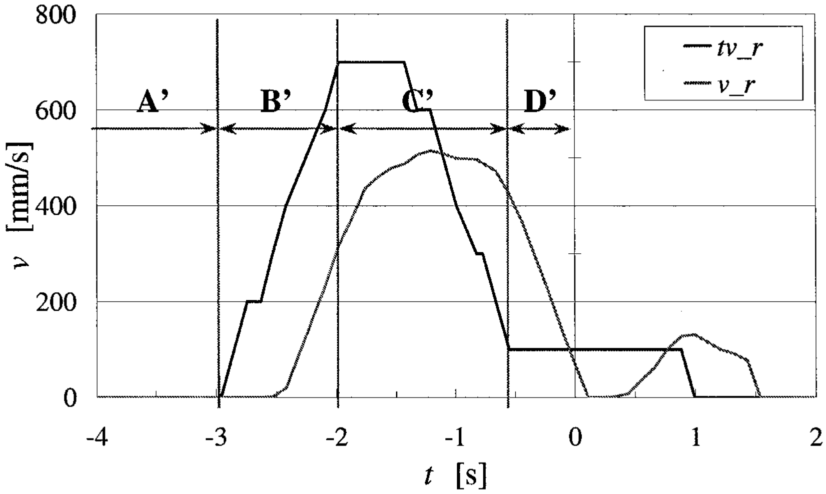


Figure 3.16: Operational task structure derived from the visually-guided tele-operation performance

Chapter 4

Analysis of Human Skill to Operate Teleoperator Robot from Ecological Perspective

4.1 Introduction

In the situations where the intermediary instruments are highly limiting their own cognitive activities to perform their tasks, human operators are required to figure out some good strategies to make up for those limitations. Tele-operation environments are indirect systems whose communicational and mechanical bandwidth restricts the human operators' perception-action cycles towards the distal events; they put bounds to the amount and quality of the perceptual information available as well as the practicable operations. Therefore, the operators confront with the considerable difficulties in developing their accurate situation awareness of the remote site and making the appropriate responses to the situations. These disadvantages need to be mitigated by some "aided eyes" or mechanical automation such as reviewed in [18, 47]. This chapter approaches this issue by analyzing skillful operational strategies acquired to compensate those unnatural conditions. Especially, the author focuses on "externalization" [58, 59], or the act performed to uncover hidden structures in the work domain onto the surface. By considering its functional utilities from the ecological perspective for human operators, the necessary information to be externalized in tele-operation environments is explored.

For this purpose, this chapter at first investigates the operational skills for the search task using a mobile teleoperator robot to find out some hidden objects under cluttered boards and boxes in the remote site. The skill analysis is done from two points of views: the one is on how skillful operational strategies organize the robotic behaviors to make the necessary but hidden information externalized onto the display; and the other is on how different operational strategies exhibit different

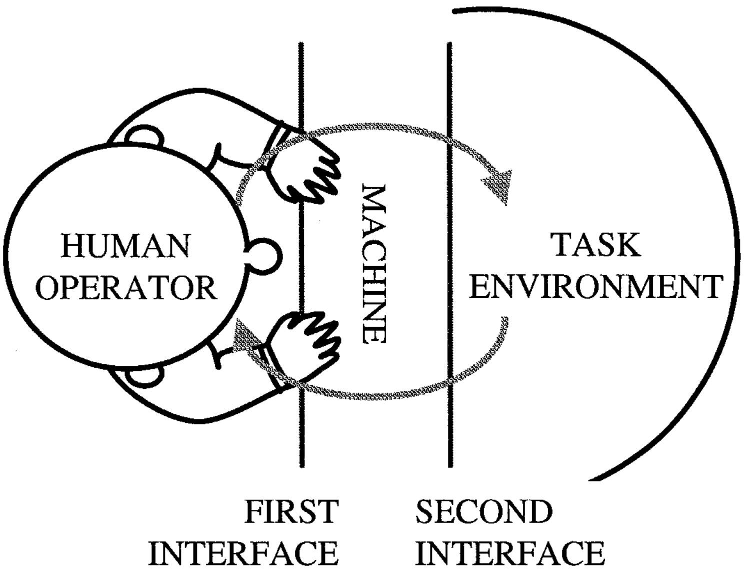


Figure 4.1: Duality of human-machine interface

manners of practicing the search procedures. After this analysis, a simple automated view control is also implemented, by which the orientation of the robotic camera is controlled in accordance with the human steering operation, and then evaluated in terms of the complementarity of human operation and automated control.

4.2 Duality of Interface and Operational Skills

When a human operator interacts with its objective environment mediated by an artifact or mechanical instrument, there should exist dual interfaces between them as shown in Figure 4.1 [40, 41]. The *first interface* represents the human-machine interface, literally located between the human operator and the machine while the *second interface* represents the machine-environment interface, through which the machine interacts with the environment. When the operator can make full use of the machine on his own, these two interfaces would become "unified" in his consciousness. As the philosopher Polanyi [34] noted, as a skill develops, the operator eventually develops a "focal awareness" of the distal as "subsidiary awareness" of the mediating chain (i.e., the components of the skill) subsides to the point that the chain becomes *transparent*. The unified interface explains this transparentized artifact, which constitutes of the operator's "extended" body and creates the phenomenological feeling in him as if he is directly manipulating the objects in the distance.

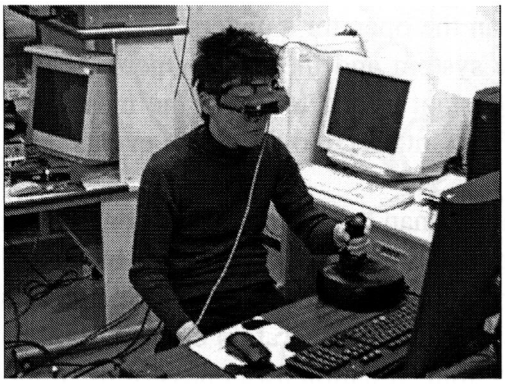
On the other hand, prior to full achievement of a skill, the operator's awareness focuses on the components of the skill. Supposing the operator must manage to employ an unaccustomed machine, the machine absorbs his focal awareness completely because the operator cannot anticipate its behaviors accurately and needs intimate feedbacks for handling. In this case, the second interface gets "far away" from his proximity in the psychological sense. The interface is the boundary through which the system including the human operator touches its external world. The cognitions derived from there mean the operator's understandings of the state of the distant interaction between the system and the environment. This "distal attribution" demands the operator's constant efforts to orient the meanings of the *proximal* information available in the first interface to the *distal* events the system brings into its task ecology.

Tele-operation environments restrict human operators' perception-action cycles towards the distal events; their communicational and mechanical bandwidth puts bounds to the amount and quality of the perceptual information available as well as the practicable operations. Therefore, the human operators confront with considerable difficulties in developing the accurate situation awareness of the remote site and making the appropriate responses to the situations. In order to make full use of such instruments, the operators must develop some skills to read off the meanings of the proximal information as the actual events on the second interface, in addition to the skills to operate the machine. Any acquired strategies to operate the tele-operation systems includes both of these aspects, and externalization [58, 59] plays an important role in them as it uncovers hidden structures on the second (i.e., distal) interface onto the first (i.e., proximal) interface.

4.3 Experimental Settings

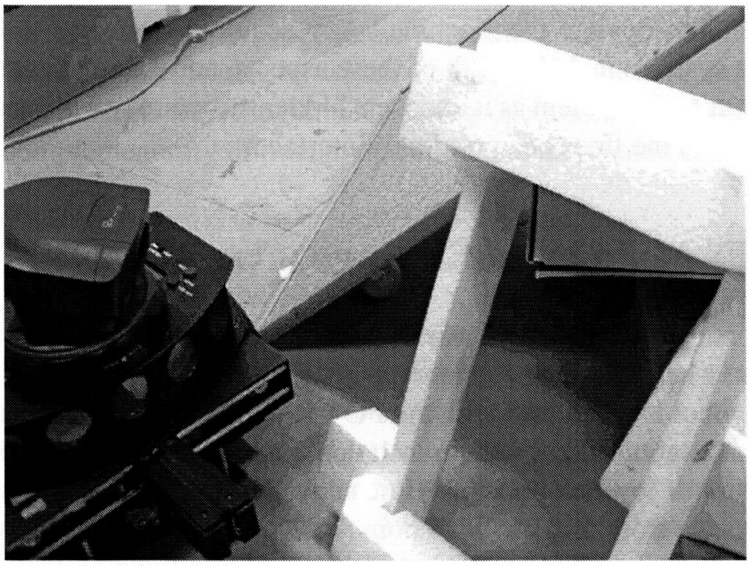
A tele-operation environment was developed for the search activity via a remote mobile robot, where a human operator navigates the robot using a joystick on a terminal PC. The robot is connected with the PC through radio modems, and its ambulatory movement is controlled by the translational and rotational velocities designated in response to the joystick position. Human available information for the navigation is the live image from the Pan-Tilt-Zoom (PTZ) robotic camera mounted on the robot, which is also controlled by the hat switches and buttons on the joystick. As it is displayed via the Head Mounted Display (HMD), the operator should comprehend the surroundings of the remote robot only from this camera image information. Figure 4.2(a) shows a scene of the human operation.

The experimental search task is to find out three objects (i.e., colored balls) hidden under piles of cardboard boxes and polystyrene forms as shown in Figure 4.2(b). Since the target objects are blinded in the recesses of the piles, the operator must locate the robot at the adequate positions so that the camera can capture them through gaps among obstacles. In all the experiments, the locations of the hidden balls were not told to the human operators beforehand.



(a) Human operation

(b) Clutters and robot



(c) A hidden object under cluttered boards (about the center of this picture)

Figure 4.2: The tele-operation environment for the experimental search task

4.4 Analyzing Operational Skills for Robotic Search Task

The first experiment was done for analyzing the operational skills for the robotic search task. In this experiment, five experimental subjects executed two different search sessions, each of which had a different configuration of the clutters. Before these performance measurement sessions, all the subjects experienced rehearsal sessions where the operators had different amount of experiences in operating the teleoperator robot. It strongly affected the differentiated search performances.

4.4.1 Comparison of Task Performance

Table 4.1 compares the search performances among all the subjects in terms of the average execution time per session (Avg. Time) and the average number of collisions the robot made with obstacles during a session (Avg. Collisions). These two measurements clarify efficiency and accuracy of the operations, respectively. More effective operations complete search in the shorter time, and more accurate operations make fewer collisions. This experimental result suggests Subject E is the most skillful among the subjects.

Table 4.1: Comparison of performances in the tele-operated search task

Subject	A	B	C	D	**E**
Avg. Time [sec]	313.5	204.5	363	148	**98**
Avg. Collisions	4	7.5	1.5	1.5	**0.5**

This consequence could be confirmed from the robotic behaviors observed. Figure 4.3 illustrates the movement trajectories of the robot in the sessions with the same clutter configuration but by different operators. The origin of this plot corresponds to the initial position of the robot when starting search the sessions. As shown in this graph, the effective and accurate operation by Subject E performed the shortest ways with neither any repairing operations due to collisions nor any oversights of passing the necessary spots to be peered. Contrary to such a skillful navigation, Subject C, who recorded the least collisions per time, drove the robot for a long distance round the clutters due to his oversights of the spots. Subject D, who completed the search task most quickly of all but Subjects E, repeated repairing operations. The other unskillful operators exhibited either or both of these awkward behaviors during their search activities as well.

Based upon these results, the skill analysis basically focuses on the distinguished operations by Subject E.

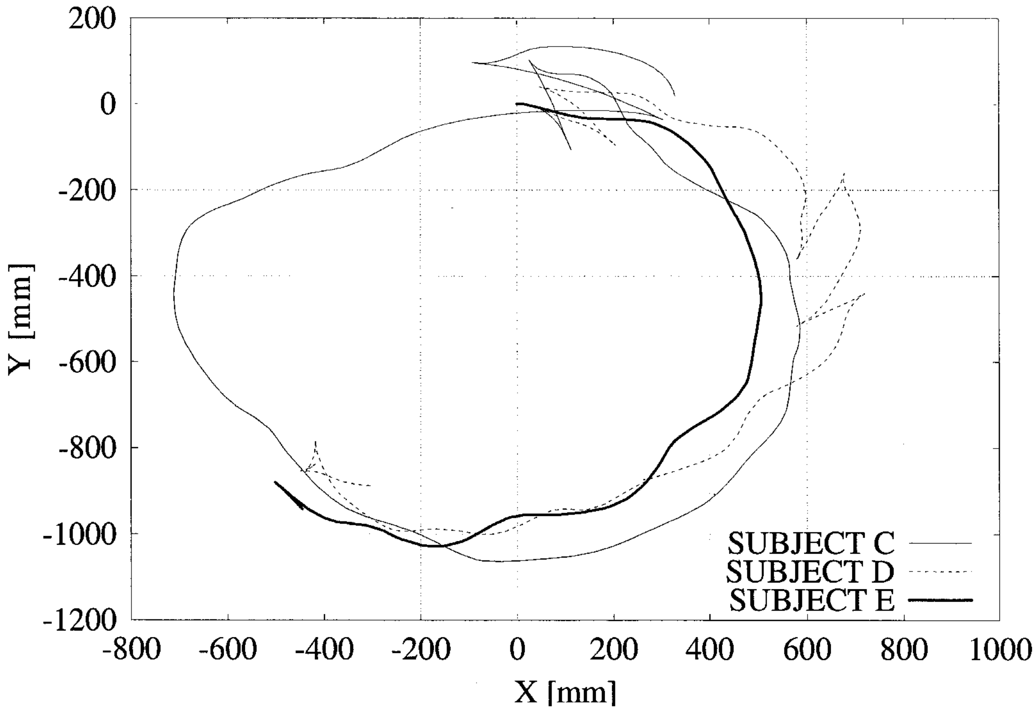
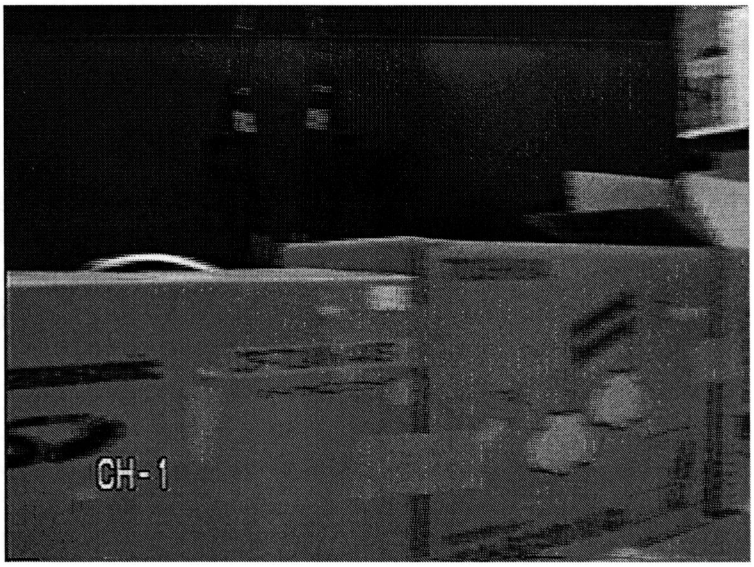


Figure 4.3: Trajectories of the robot compared among sessions of a same clutter configuration but different operators

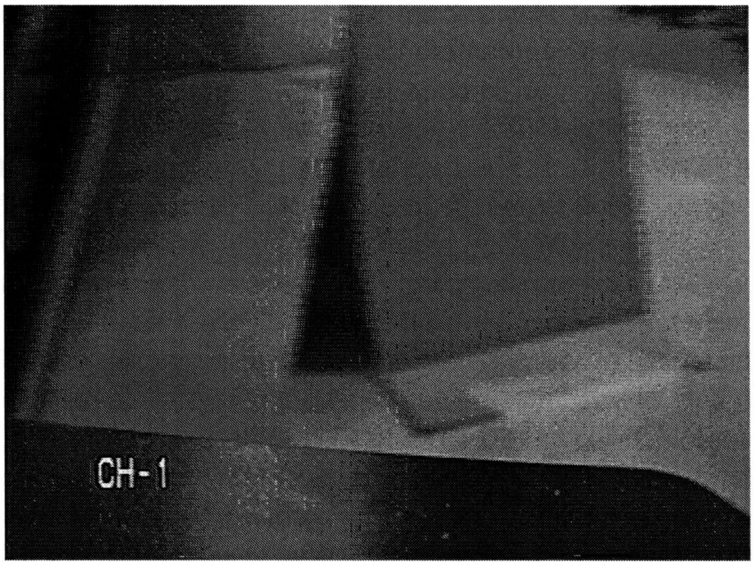
4.4.2 Analyzing Optical Flows in Turning Operation

As the target objects are blinded by the piles, the operators must locate the robot at the adequate positions so that the view camera can capture them through the gaps of the piles. During navigation toward such a position, the robot needs to make the round of some covering objects. Distinguished operational skills for navigating the robot were observed particularly in this situation.

A typical robotic behavior which can differentiate levels of the operational skills is the way to allocate the camera's field of view while the robot is making the round of some objects to a certain destination. Figure 4.4 compares a snapshot from the Subject E's view with the Subject A's during a turning operation. On the one hand, a common strategy among the unskilled operators renders the robotic camera direct to its home position always before any travels of the robot as illustrated in Figure 4.5(a). Keeping the camera front affords easy perception of "ego"-locomotion from the view images, and thus gives easy correspondence of direction between stick-handling and ambulatory movements in the operator's cognitive map of the search site. This operational strategy, however, provides no clue during a turn as to the relationship between the robot itself and its surroundings from the live image of the view camera which is the only source of the information on the search area (see

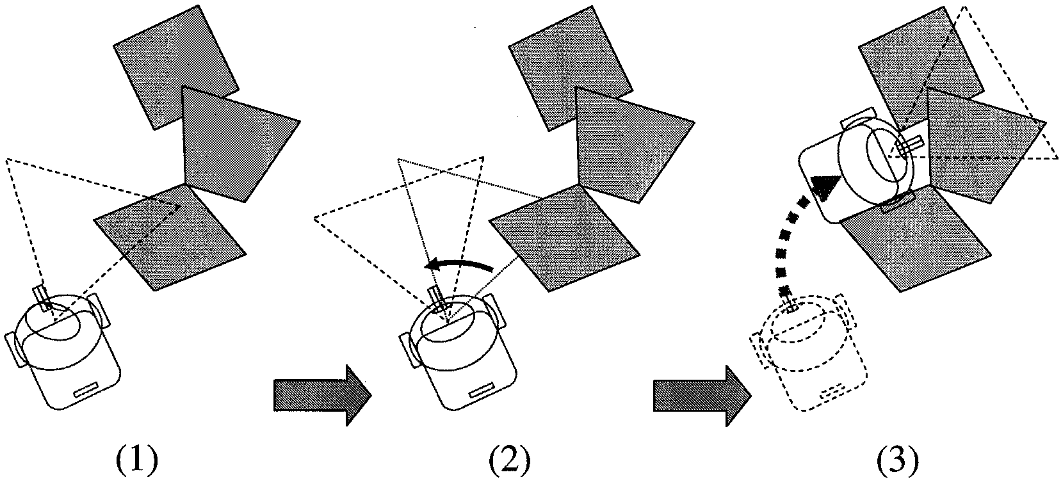


(a) Subject A (unskilled operator)

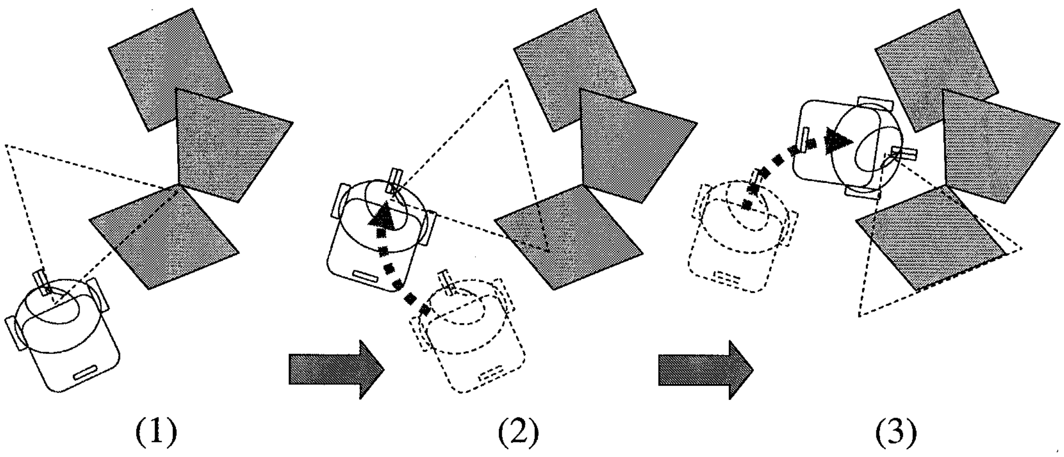


(b) Subject E (skilled operator)

Figure 4.4: Comparison of two camera views between Subject A and E, each of which is a snapshot during the robot making the round of some covering objects



(a) Unskillful operation



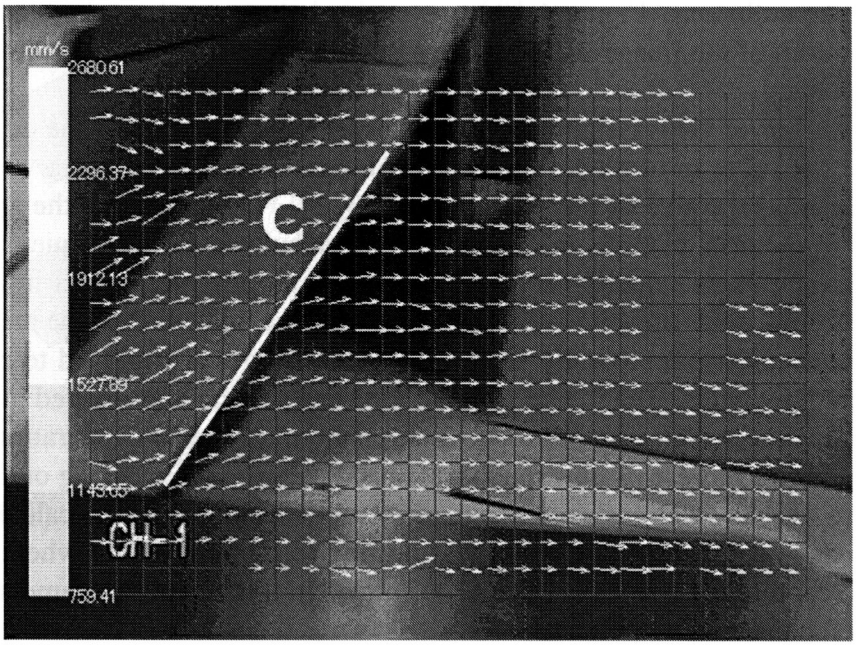
(b) Skillful operation

Figure 4.5: Different operational strategies when the robot makes the round of some objects to a certain destination

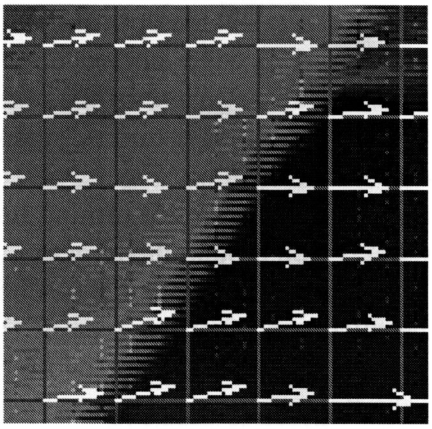
Figure 4.4(a)). On the contrary, as shown in Figure 4.5(b), the operational strategy of the Subject E orients the camera suitably to keep in sight both the robot's body and the objects that may become obstacles to its travel, thereby realizing fewer failures like collisions. Figure 4.4(b) proves this behavior, where the black region on the bottom of the image indicates the top left edge of the platform the camera was mounted on.

This clever view assignment was also well-coordinated with the driving behavior of the robot in turning operations. View images of the camera were analyzed from the perspective of the *optical flow* [13, 24]. Optical flows, the apparent motions of pictorial patterns in images, can be calculated from a sequence of images and presented as velocity vector fields. When an observer moves in a 3D world, optical flow fields are generated on his retina. Here, matching of the brightness pattern between two temporally successive video frames is deployed to calculate the optical flow fields. The image plane of the view camera was divided into quadratic cells, each of which corresponds to a unit pattern of matching operations. Each velocity vector represents how much a pictorial pattern moves during one frame time. Figure 4.6 shows an instance image of the optical-flow analysis, calculated from a sequence of images as the robot was turning to the destination where the camera could capture the space the edge C occluded. In this scene, the camera was seeing the left hand side of the robot.

The optical-flow analysis revealed that the Subject E's operational strategy had successfully adjusted turning movements of the robot to keep the target of its travels in sight all the while. Figure 4.7 gives another instance image from the same optical-flow analysis. We can see that the optical flow around the target of the turning movement (i.e., the occluding edge labeled as C in Figure 4.6) is flatter than outer regions'. This means that the image of the target does not flow so much in the field of view even while the robot is turning, thereby making it easy to locate the robot in the course to the destination. Figure 4.8 compares the averaged magnitudes of the optical flows during a series of turning operation between two regions in Figure 4.7; Area A, the region around the target of turning, and Area B, its outer region. More steady flow around the target can be confirmed as well from the profile of Area A than the fluctuating flow of Area B. Optical flow fields, by nature, provide significant cognitive resources on the "ego-motion" [13]. As shown in Figure 4.9, the source of the flow springing out corresponds to the direction to which the observer is traveling. This invariant structure in the visual information affords an observer to adjust his locomotive behavior toward an intended destination by bringing the traveling direction into a point with the intended destination in his visual field. The result of Figure 4.7 is comparable with this behavior, and then it is interesting that human adaptation achieved a perception-action coordination analogous to the ordinary one on a daily basis, even in the unnatural conditions of a tele-operation environment. The unskilled operators, on the other hand, direct the camera to its home position before any travels of the robot, and therefore this type



(a) An analysis image of optical flows



(b) Enlarged illustration of the above image

Figure 4.6: An instance image from the optical-flow analysis

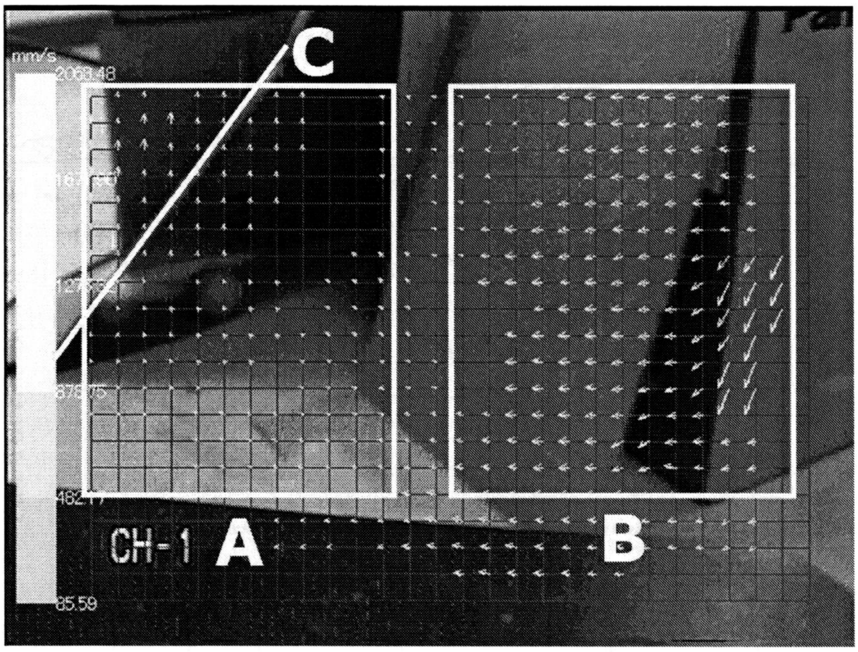


Figure 4.7: Another instance image from the optical-flow analysis: the optical flow around the target of the turning movement (i.e., the occluding edge C) is flat

Figure 4.8: Comparison of the averaged magnitudes of the optical flows between the Area A and B

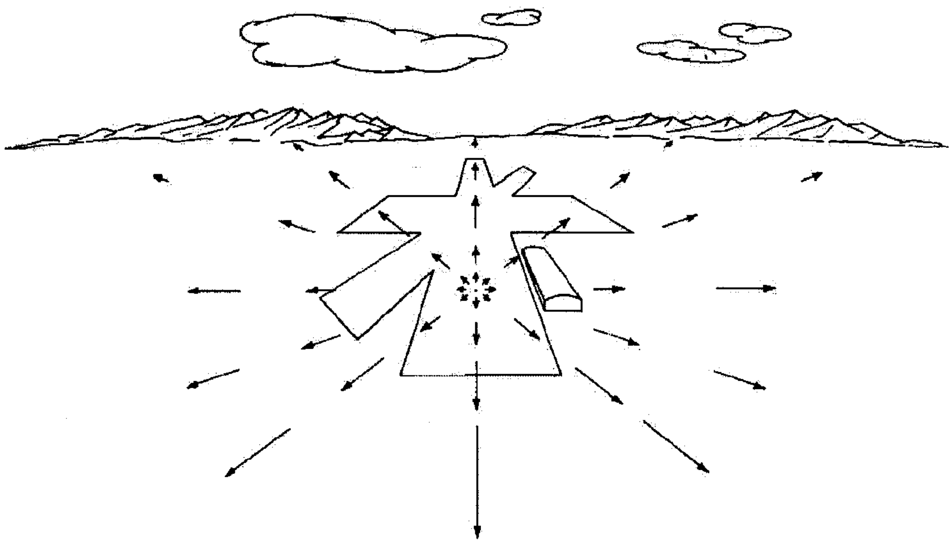


Figure 4.9: Optical flow and ego-motion perception (from [13])

of perceptual structures did not appear in a sequence of their visual information.

As explained above, the skillful operational strategy Subject E acquired achieves two important externalizations for orienting the observer (i.e., the *joint* cognitive system of the human operator and the robot) in the task environment. The one is to expose part of the robotic body to the vision camera, by which the physical relationship between the observer and its surroundings is directly measurable from the visual information. The other is to shape meaningful structures (i.e., the optical flow) in the fluid visual information by adjusting ambulatory movements of the robot.

4.4.3 Time-Series Decomposition of Human Operations

The next analysis is performed to clarify how different operational strategies exhibit different manners of practicing the search procedures. In this analysis, a series of human operations is decomposed into a concatenation of some activity phases in which basic subordinate activities are (in)activated in parallel. For this procedure, three typical activities, which compose of the activity phases, are defined in response to the measurements and patterns in the human controls. Their definitions are given as follows:

- **ACT1—Driving Robot:** This activity aims to drive the robot toward a destination where it should look for the target objects through the gaps of the piles, i.e. ACT3, or toward somewhere opened to look around for the next destina-

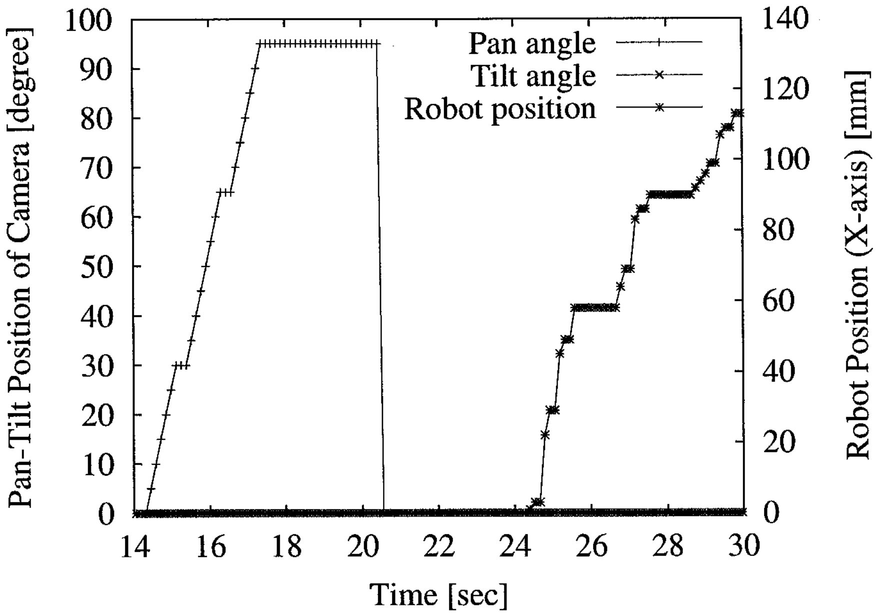


Figure 4.10: A typical transition pattern of the robotic camera's Pan-Tilt angles and X-coordinate value of the robot's position during ACT2 (from profile data of operations done by Subject C)

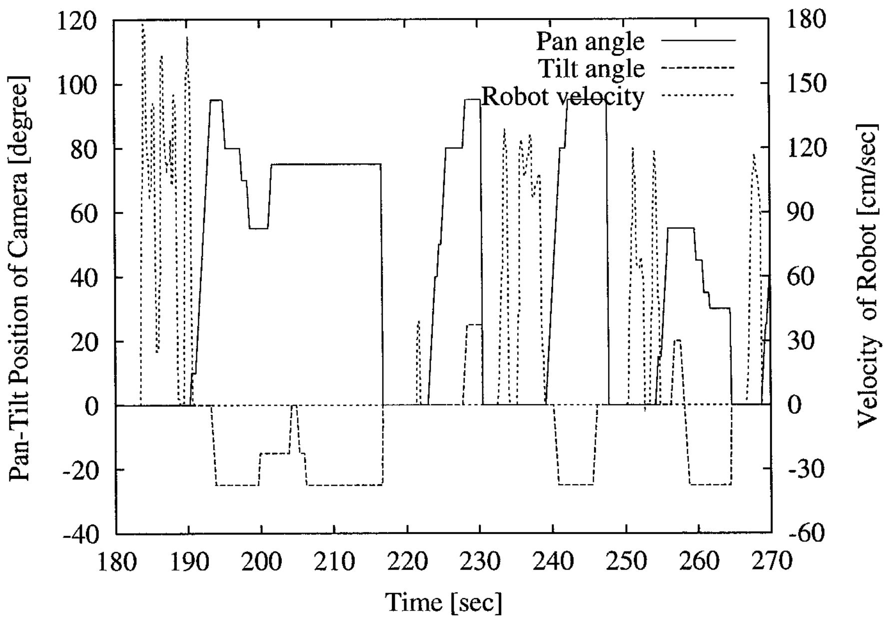


Figure 4.11: A typical alternation pattern of locating the robot and orienting the camera during ACT3 (from profile data of operations done by Subject C)

tion. During this activity, any collisions with obstacles should be avoided.

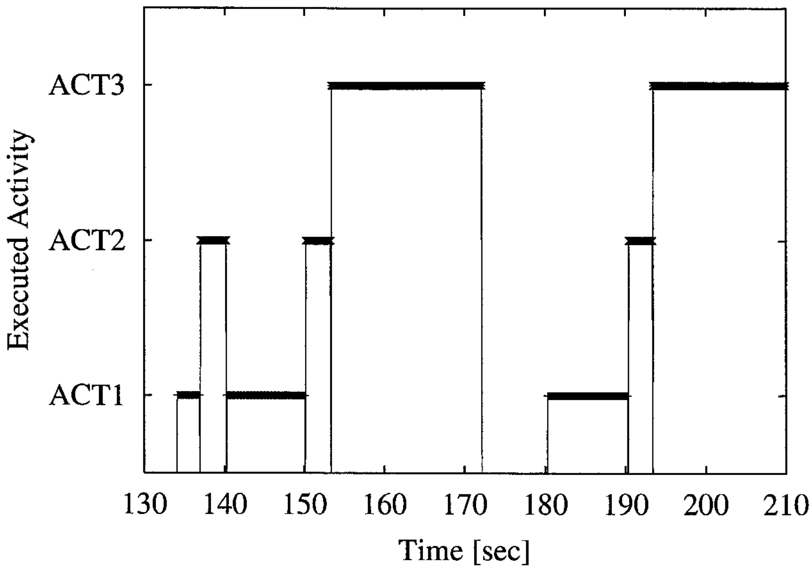
- **ACT2—Recognizing Situation:** This type of activity corresponds to panning the robotic camera with no steady gaze on a certain region, thereby seeing the picture of the situations. The purpose of this physical operation can be classified into the two classes. The one is to confirm a safety distance to be kept from obstacles for avoiding collisions when the robot is turning. The other is to fix a plausible location where a target(s) would be found. However, because it is difficult to discriminate these two intents from the measurable data, they are dealt with the same category of activity here. A typical transition pattern of the measurements during this activity is shown in Figure 4.10, wherein time-series data of the camera's Pan-Tilt angles and the X-coordinate value of the robot's position are included. Its important diagnostic character is the absence of "look down" operations[1], i.e. holding the Tilt angle to zero, while operating either Pan or ambulatory motions.

- **ACT3—Seeking for Targets:** This activity aims to look for the target objects by moving the camera or the robot around the location where the operator is anticipating them. During this activity, orienting the camera on a certain region and adjusting the robot's location are "alternately" performed. Figure 4.11 shows a typical profile of such alternation by Subject C, in which some tilt-down operations are observed by contrast with the profile of ACT2. In this profile, we can recognize the operator's engagement in this seeking activity with many little ambulatory movements (i.e., up-and-down transitions of the robot's translational velocity) and his attempts to peer down by turns.

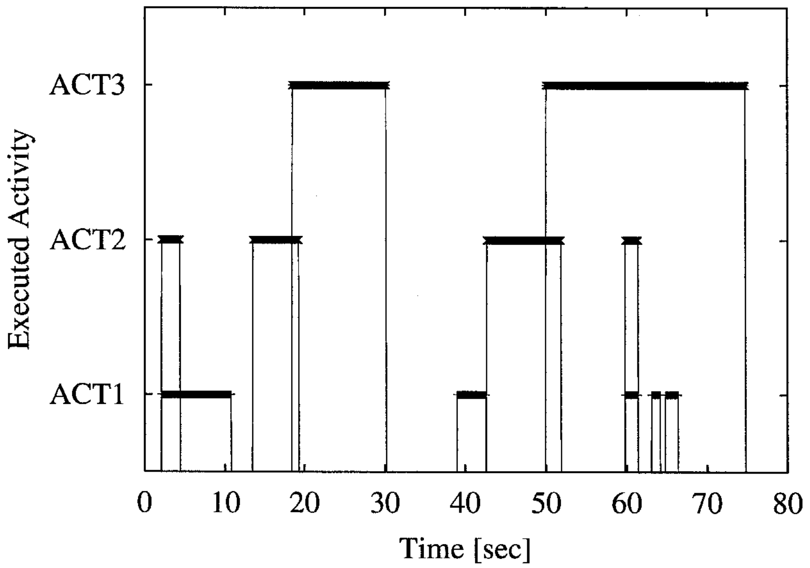
According to the above definitions, profile data of human operations were taken apart into the progress charts of those sub-activities. Figure 4.12 plots and compares two search operations of different skill levels. Each profile is partitioned by the (in)activations of the three sub-activities, i.e., ACT1, ACT2 and ACT3, allowing their temporal overlaps. This comparison reveals that the most remarkable feature of the skillful search by Subject E is the parallel execution of two or more different activities (Figure 4.12(b)). Contrary to this behavior, Subject C performed its completely sequential execution of those activities (Figure 4.12(a)). This tendency of the serialized search activities was observed in the operations by all the other unskillful operators as well.

A typical evidence of these different styles of search behaviors was observed in the way to allocate the camera's field of view while the robot is running round some objects to a certain destination as discussed in section 4.4.2. As a common strategy among the inexpert operators, they always direct the PTZ robotic camera

[1]As the PTZ robotic camera is mounted on the top of the mobile robot, it should look "down" something on the floor like a target object in our experiments.



(a) Subject C (unskilled)



(b) Subject E (skilled)

Figure 4.12: Comparison of two search operations of different skill levels in terms of (in)activations of the three sub-activities

to its home position before any travels of the robot. Therefore, they have no clue as to the relationship between the robot and its surroundings from the live image of the camera during a turn. On the contrary, the Subject E's operational strategy, in which the camera is oriented to keep in sight both part of the robot's body and the objects that appears to be obstacles to its travel as shown in Figure 4.4(b), realizes the parallel execution of ACT1 for the robot driving and ACT2 for the situation recognition. This should lead to his fewer failures like collisions.

Separated executions of driving, recognizing, and seeking activity should cause disjunction of behavioral contexts which are basically supposed to be chained for smoothing search behaviors. They switch over from one configuration of cognitive resources for the human operators to another, due to the limitation of available cues on the surroundings of the remote robot through the onboard camera. Therefore, it can be considered as the reason why the unskilled operators can not achieve both criteria of efficiency and accuracy of the robot navigation together.

4.4.4 Coping Strategy to Perceptually Impoverished Conditions

Basically, the act to drive the robot has two different meanings in the search context. The one is to purely and simply move the robot to a certain destination that has been planned at once or in advance. The other is to retrieve novel cues from perceptual information that is varying during movements, so as to enrich the operator's recognition on the environment, which is closely connected with the activity of ACT2.

Concerning this duality, Kirsh has proposed the concept of *epistemic actions* [28, 29] as distinguished from *pragmatic actions* which bring the actor physically closer to its goal. Epistemic actions are physical actions as well as pragmatic actions, but their primary function is to improve cognition. Thus, they are performed to uncover some hidden information which is hard to compute mentally but necessary to the actor's correct recognition on the task ecology. Those exploratory actions render a efficient coping strategy for overcoming perceptually impoverished conditions, which play an important role in our human flexible and skillful performances in the complex real world [26]. At the same time, those actions are essentially "situated" [51], or highly context-dependent. Serialized operations by the unskilled operators, however, segmentize their behavioral contexts, and thus demand some conscious processes for themselves to concatenate those context segments via "mental arithmetic". The analytical result of the awkward search behaviors by the unskilled operators here explains that they were in difficulty to perform such *situated* actions. This is an example where the tool itself (i.e., the robot tele-operation system) constrains and transforms the users' behavioral strategies apart from their natural ones.

Contrary to this, the most experienced operator, i.e., Subject E, could accommodate himself to those constraints enough. He developed a new operational strategy to appreciate some invariant structures externalized in the visual information, which

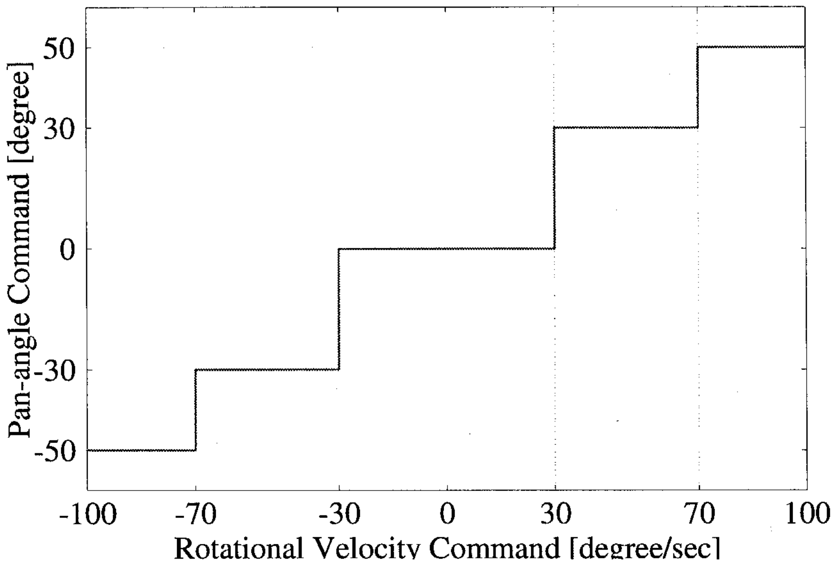


Figure 4.13: Correspondence map used in the automated view control according to the wheeling (i.e., the rotational velocity) commands by a human operator

help him overcome the difficulty to accurately locate the robot in the task environment. This strategy may be a specific product, but surely contributed to accurate and efficient search operations, repairing the psychological distance between a human operator and its objective environment.

4.5 Shared Control with Machine Autonomy for New Perception-Action Coordination

The skill analyses in section 4.4 brought out that the skillful operations are evidently different from the unskillful ones in the way to control the viewing field of the camera during ambulatory movements of the robot. The operator of the highest performance utilized more effective views for unfailing operations with his accurate situation awareness than the other operators did. One exemplary strategy observed in the experiment was to orient the camera toward the current traveling direction while the unskilled brought it back to home position before any travels. Based upon this result, the second experiment is prepared to examine the effect of a new perception-action coordination introduced into the robotic search behavior, which aimed to simulate such skillful view control.

4.5.1 Behavioral Design of Automated View Control

Simple machine autonomy to control the viewing field of the robotic camera was installed into the tele-operation system. The autonomy complies with a pre-determined coordination of the view with the traveling direction, and functions when the robot is making the round of some objects. The correspondence map designated in Figure 4.13 is utilized to translate the ambulatory motion commands (i.e., the rotational velocity of the robot) by a human operator into the view control commands (i.e., the Pan-angle of the camera). Because all the ambulatory motion commands have an effect on the robot if and only if the operator holds the trigger switch on, the operator can independently manipulate the viewing direction the camera while the robot remains stopped at a place. Otherwise, the human operator and the machine autonomy share the control of the robot.

4.5.2 Effects of Automated View Control

All the experimental subjects did another two search sessions with different clutter configurations. This experiment revealed that interventions by the above autonomy had better or worse effects to respective operations. Table 4.2 presents part of the result, comparing search performances of the human-machine shared control in this experiment with the ones in the manual control (i.e., in the first experiment).

Table 4.2: Comparison of search performance between manual and shared control

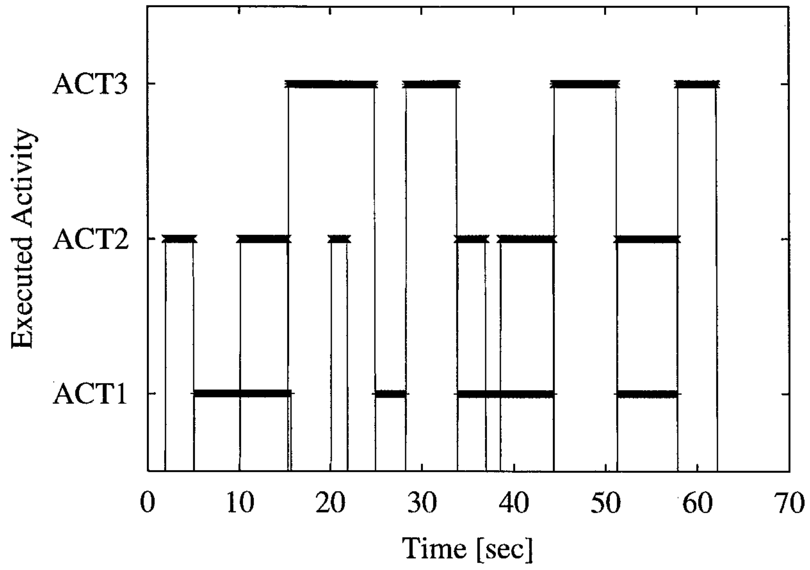
Control Mode	Manual	Shared
Avg. Time [sec]	313.5	105
Avg. Collisions	4	0.5

(a) Subject A

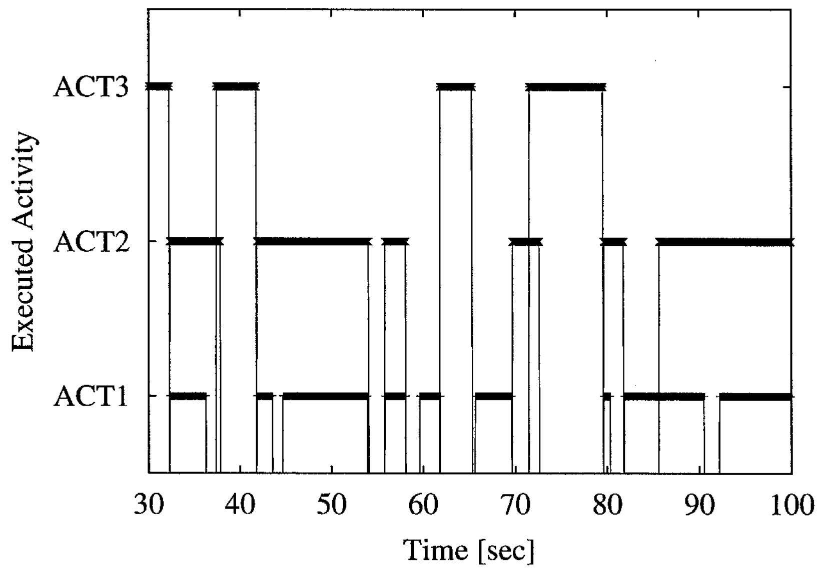
Control Mode	Manual	Shared
Avg. Time [sec]	98	190.5
Avg. Collisions	0.5	5

(b) Subject E

On the one hand, Subject A recorded much more effective and accurate searches in the shared control environment as shown in Table 4.2(a). In addition, he expressed his positive feeling on the automated view control in the interview after the experiment, in that the autonomy could successfully expand his vision by providing good opportunities to capture the effective resources for his situation awareness when driving the robot. His remark was also confirmed by the analysis of his op-



(a) Subject A



(b) Subject E

Figure 4.14: Analytical results of operational profile data in the shared control environment

erational profile data into the sub-activity progresses after the same method in section 4.4.3. Figure 4.14(a) presents an instance of this analysis to the Subject A's search behavior, indicating several co-occurrences of ACT1 and ACT2. Hence, active interventions by the autonomy might promote the development of his new perception-action coordination that can exploit new cues never available before.

On the other hand, the Subject E's performances got dramatically worse by the interventions (Table 4.2(b)). This result is to be expected because his operational strategy had been nearly perfect in terms of our experimental task and thus surely collapsed by any interventions. Figure 4.14(b) shows his deformed operational strategy (cf. Figure 4.12(b)). The autonomy introduced unexpected behaviors from his perception-action coordination, and disappointed his anticipations on what to be seen after his operational inputs. This should make it harder for the operator to take any situated actions for more accurate recognition of the situations.

The other class of results was also observed with neither better nor worse effects of the machine interventions. Although these unclear results explain insufficient considerations of the autonomy design of course, every automation should hold this type of incompetence because the two perspectives to the automated system do not agree with each other completely between the *external* designer and the *internal* user (i.e., a type of "frame-of-reference" problem [33]). From this point of view, some kind of "personalization", like behavioral adaptations of the machine autonomy through work experiences with a user, would be expected when implementing skill supports.

4.6 Summary

This chapter investigated human skills to operate a mobile robot in a tele-operation environment, where the human operators confront with considerable difficulties in developing their accurate situation awareness of the site explored remotely and making the appropriate responses to those situations. The experimental results revealed that the most accurate and efficient operator realized a clever control of the view camera, which enabled the parallel execution of the two different activities for moving the robot and for developing the accurate situation awareness. This operational strategy was analyzed from the two points of view. The one is on how skillful operational strategies organize the robotic behaviors to let the necessary but hidden information externalized onto the display. This analysis was done based upon the optical-flow analysis of view image from the onboard camera during a series of ambulatory movements around covered objects. The other analysis is on how different operational strategies exhibit different manners of practicing the search procedures, and was performed by decomposing a series of operations into the transitions of some subordinate activities. In order to make full use of the teleoperator robot for the search tasks, the operators must develop the skills to read off the meanings of the proximal information as the actual events in the distance, in addition to the ones to operate the robot. Both of the analyses explain that what's necessary to be externalized is the information for accurately orienting the remote robot in its task environment.

Chapter 5

Design of Shared Communicational Modality between Human and Machine Autonomies

5.1 Introduction

There proposed an idea of "shared autonomy" as a new concept of human-machine collaboration styles, which expects to encourage the reciprocal complementarities emerged in their joint activity [18]. Unlike supervisory control in which a task of interest is hierarchically divided into the upper knowledge-level (e.g., planning) and the lower behavior-level (e.g., plan execution) that are assigned to humans and machines respectively, this style of human-machine collaboration intends their independent and parallel contributions to both levels of the task. Therefore, this concept stresses the design philosophy that a human- and a machine-*autonomy* should collaborate with each other as *equivalent* partners, while its comparable concept of "shared control" [47,48] simply denotes the concurrent mixture of human operation and mechanical control. Shared autonomy suggests a very important perspective on how to couple together a human user and a machine with highly advanced automated functions toward their good relationships, but it still remains at the conceptual.

The essential differences in physical and cognitive capabilities between humans and machines can contribute to providing different accesses to an identical task situation, and so can enhance the total system performance. "Mixed-initiative interaction" [1] represents the style of interaction between the subjects collaborating with each other, where their roles and initiatives are not fixed in advance and appropriately assigned depending on the situations (see section 2.4). Composing mixed-initiative interaction between human and machine agents has large potentials toward the truly effective human-machine collaboration [11,12,20]. However, any interventions by other than his/her own decisions may be the factors to disorder human control. They could hurt operationality of the system from the operator's perspective by introducing unexpected behaviors into the system. Thus, in order to realize naturalistic collaborations in such human-machine systems, we need to explore the effective way to establish and maintain the correct understandings on their common task situation shared between them, especially, the way to let the human operators adequately recognize interventions by the machine autonomy into their own operations. This is a key issue on human-machine interface design.

Concerning this issue, this chapter provides a formal approach to designing human-machine interaction channels between a human operator and a machine autonomy. Based upon the classification scheme of information types defined in Kirlik's *Generalized Lens Model* framework, a shared-control environment by a human operator and an autonomous mobile robot is investigated at first. This analysis brings forth a new human-robot collaboration style with the *shared communicational modality* between a human operator and a robot autonomy. The proposed model of human-robot interaction is implemented into an actual tele-operation environment, and then evaluated in terms of the mutual relationship of the cue-utilization strategies between the two as well as their joint task performances.

5.2 Mutual Understanding through Socially Epistemic Actions

As clarified in the design principle of *ecological interface design* [52,54,55], human-machine interface designs must be coherent with the ways of human thinking and perceiving performed under their bounded cognitive resources. In relate to this philosophy, we know an important empirical fact that action plays not only a *performatory* role but also an *exploratory*, or knowledge-granting one [26,28,29]. This latter aspect of action, referred as "epistemic action", plays an very important part in our human flexible, skillful performances in the complex world because it is an efficient strategy to reduce their cognitive burden such as inferring some indepth structures of their work domains [26].

This prospect is also supported by Neisser's theory on human cognition, i.e., his view of *perceptual cycle* [31]. He argued that knowledge in the form of schemata, or mental models, leads to anticipation of certain kinds of information. As such, the observer's active schemata mentally structure the flow of events; they effectively direct exploratory movements, and increase receptivity to particular aspects and interpretations of the available information (see the inner circle in Figure 5.1). Meanwhile, as the data that the observer samples or picks up from the environment are absorbed by the schema, they serve in turn to modify or update the information and events that the schema is prepared to receive next. Continuous wheeling of this

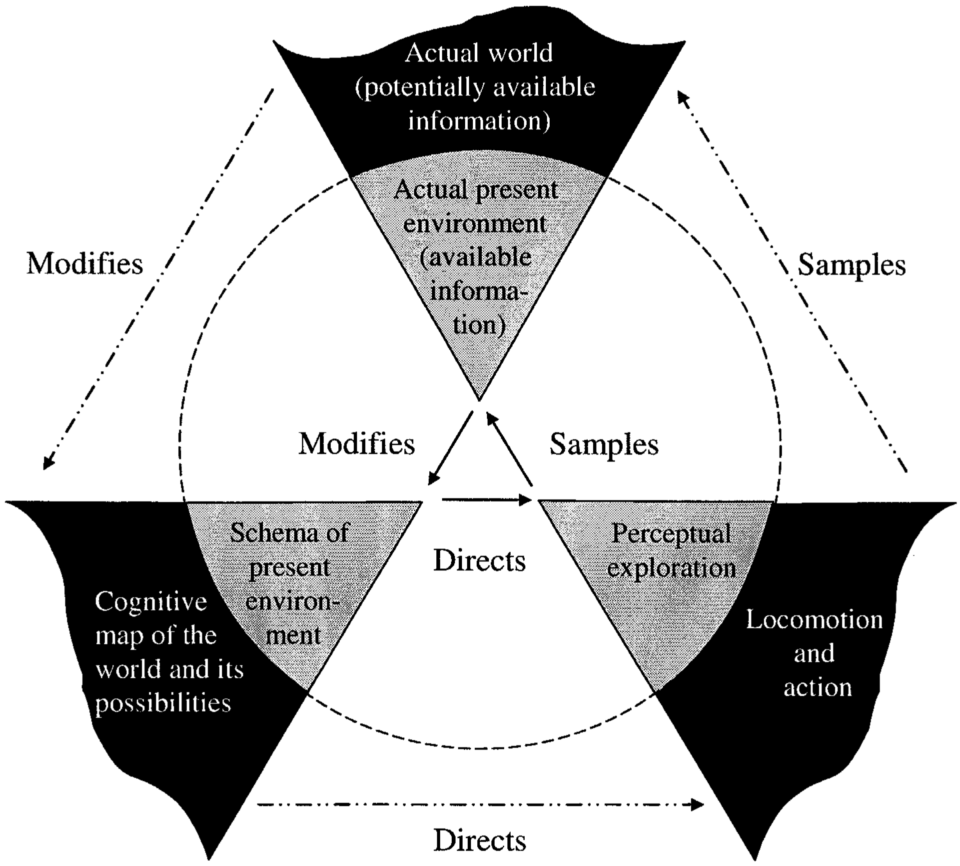


Figure 5.1: Neisser's view of the perceptual cycle (from [31])

exploratory cycle represents that the observer's smooth interaction with the environment is achieved. At the same time, the exploratory processes in the observer will sometimes uncover data that the schema does not expect, or they will fail to find data that it does expect. In those cases, more general exploratory cycles are required including actions taken to obtain information that is not present in the immediate environment. The outer circle in Figure 5.1 represents such physical interaction with the environment. This big picture of the "unbroken" cycle represents the essential nature of our cognitive activities when interacting with our ecology. They require the perpetual connection and interaction with the external world, therefore in which epistemic actions are responsible for valuable exploratory movements to verify the anticipation.

In conventional human-machine systems designs, actions of human operators are extremely limited in the control loop of the highly automated systems due to their admissible disturbances for stable, reliable, or efficient operations. However, in order to encourage their naturalistic collaboration emerged in their joint activity, those systems should provide some effective ways to let each agent (human or

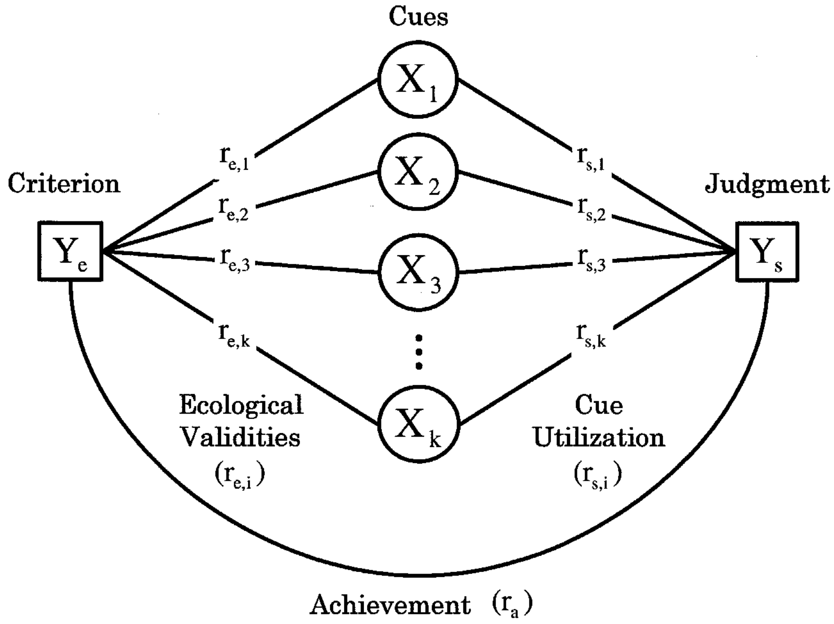


Figure 5.2: Brunswiki's Lens Model

mechanical) adequately be aware of what the partners are doing and going to do. Hence, the author's fundamental philosophy for this purpose is that any collaborative systems need to accommodate each agent's (human or mechanical) variable actions including their epistemic actions.

5.3 Conceptual Scheme of Shared Communicational Modality

As discussed in section 2.4, good human-machine interfaces provide some bilateral information channels, through which both humans and machines can exchange their exploratory acts to adjust their judgments to each other. Toward the realization of such interface systems, this section provides a systematic approach to designing effective communication channels, named *shared communicational modality*, in shared-control environments. The proposed approach makes use of the classification scheme of information types defined in Kirlik's *Generalized Lens Model* framework [26], thereby depicturing the latent covariant relations among variables involved in the human-machine system.

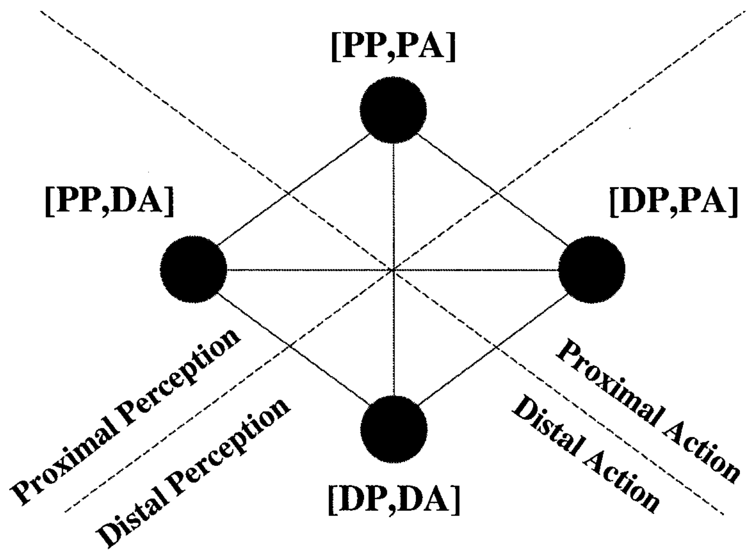


Figure 5.3: Kirlik's Generalized Lens Model (from [26])

5.3.1 Lens Model and Its Extension as Analytical Methods

Brunswik's Lens model is a functional representation of human perception and judgment [4,6,15,48] that can describe their causal relationships without separating his/her internal and external state. As shown in Figure 5.2, this model provides dual symmetric models of a human judge (*subject*) and its environment (*ecology*). The *judgments* and the *ecological criterion* to be judged are described as combinations of *cues*, or available information in the environment. In this way, both the judgment policy and the environmental structure in terms of the cue-criterion relationships are captured as the *cue utilization* and the *ecological validity*, respectively.

This model makes the *proximal versus distal* distinction in human perception. The "proximal" refers the direct accessibility by the judge while the "distal" represents the indirectness and is accessed through the proximal information. Hence the criterion is distal because the judge cannot directly perceive it and has to infer it from the proximal cues directly measured. This distinction is only about perception but not about action. As the model describes the view of the subject without any control over the environmental structure, it is insufficient to deal with the "proactive" human-machine interactions including epistemic actions. Concerning this deficiency, Kirlik has proposed to add the proximal-versus-distal structure of action into the Lens Model as his *Generalized Lens Model* in [26]. Figure 5.3 illustrates this model. With this extension, variables in the task environment are classified into four different types as enumerated in Table 5.1. In addition to this classification scheme, the model has a potential of constraint relations among these classes of variables as indicated six lines connecting the four variable types in the figure.

The Lens Model formalism also has some parallel indices called *Lens Model*

Table 5.1: Four different types of variables in Generalized Lens Model

Variable type	Definition
[PP,PA]	a variable that is proximal for both perception and action.
[PP,DA]	a variable that is proximal for perception but distal for action.
[DP,PA]	a variable that is distal for perception yet proximal for action.
[DP,DA]	a variable that is distal for both perception and action.

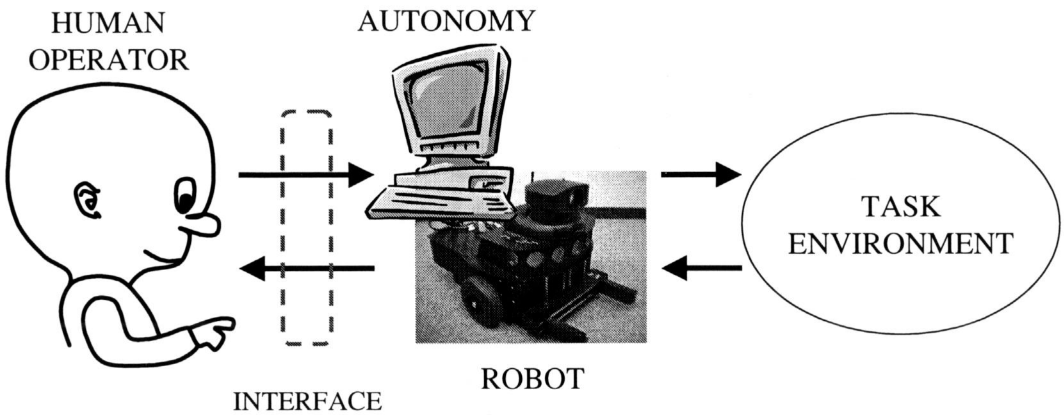


Figure 5.4: A shared-control system in which both a human operator and a robot autonomy contribute to the control of a mobile robot

Equation (LME) Parameters [6]. They are utilized for further investigations on interactive systems in terms of quantitative evaluations, such as the extent to which a human judge makes judgments consistently. Detail explanations on this formalism including definitions of those parameters are presented in Appendix A.

5.3.2 Creating Bilateral Information Channels with Mutual Behavioral Constraints

After the qualitative classification of information types defined in Kirlik's framework, variables in a shared-control environment are distinguished in terms of "proximal or distal" from both perspectives of perception and action for each decision-maker in the system. Figure 5.4 illustrates the shared-control environment to be analyzed here, in which both a human operator and a robot autonomy contribute to the control of a mobile robot.

Figure 5.5 gives a general depiction of variables and their relations involved in the system control. Two autonomies in the system, i.e., a human operator and a robot autonomy, have their own intentions to control the robot. Those intentions are to be judged as criteria since each of them is [DP,DA] from the other's point of view. The interface system between the autonomies then mediates the two

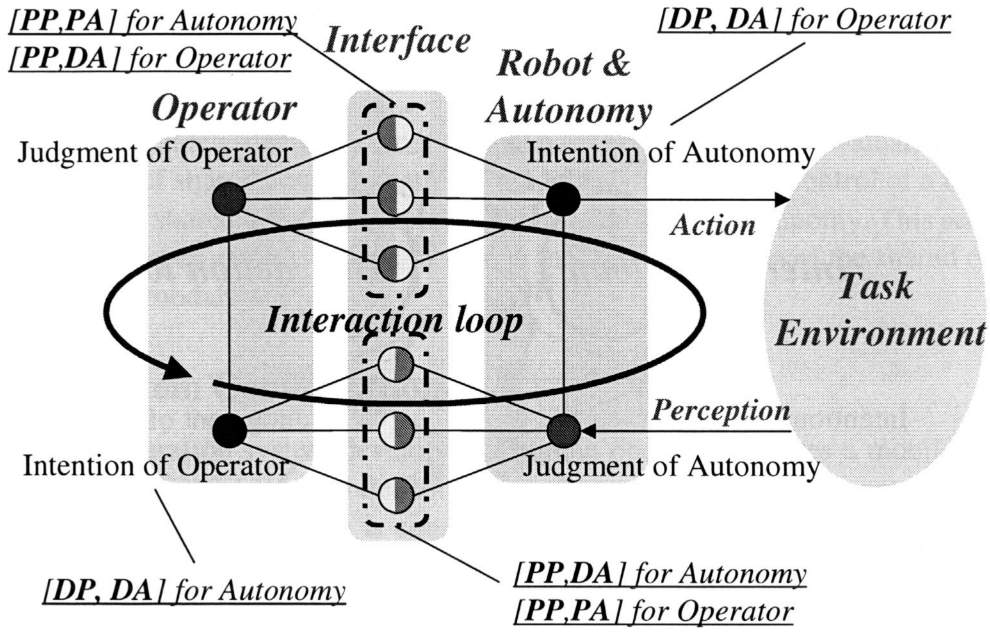


Figure 5.5: Depiction of variables and their relations involved in a shared-control system

judgment-criterion structures represented as the two lens structures in the figure. Some variables on the interface are [PP,DA] from one perspective as they provide cues for the judgments about what the partners are intending to do. The same variables can also be seen as [PP,PA] from the other perspective because they reflect manipulations by respective autonomies. This dualism of variable functions is expressed by two semicircles clinging together in the interface domain.

So as to develop a common understanding of the situations in their task environment, both autonomies should be aware of what their partners are doing and going to do. Thus, socially epistemic actions will be exchanged in their joint activity to explore the adequate "team situation awareness" for their collaboration. Considering information flows in the system from this point of view, an exploratory process initiated by the human operator can be represented as the large interaction cycle at the center of the diagram. As this cycle involves several intermediate processes including the physical interaction between the robot and the task environment, no immediate feedback from the partner about the operator's exploratory acts is available. Therefore, the operator should confront with great difficulties in probing the autonomy's decision structure, or judgment policy. He must specify the actual responses to his epistemic actions out of ill-organized data with extra and/or delayed behaviors mixed in. Moreover, collaborations by independent autonomies, in principle, demand common and strong information resources to be shared for establishing coherent and consistent judgments between them, but there are no such resources in

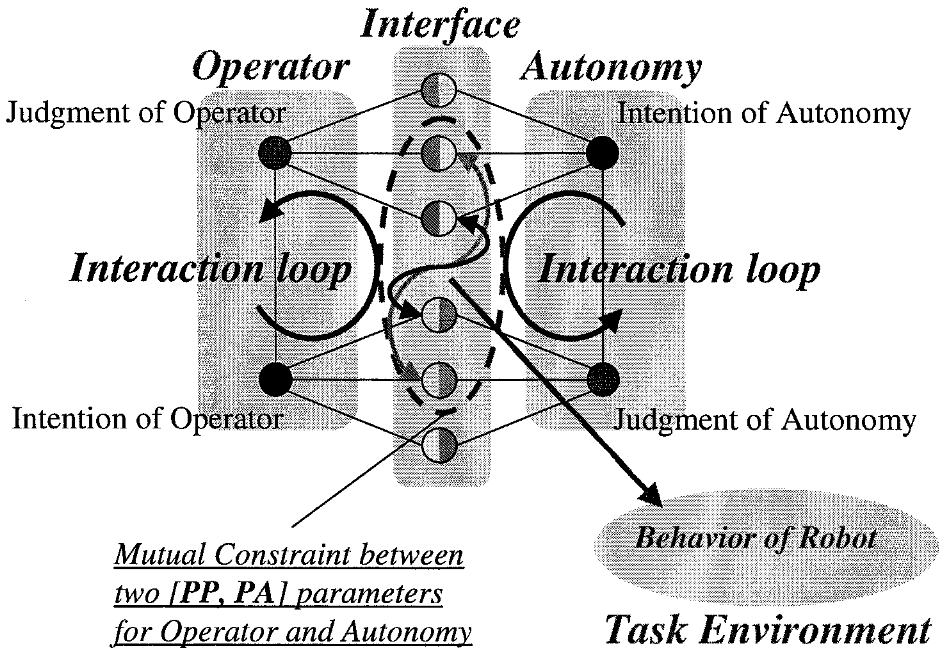


Figure 5.6: Enriched interaction cycles through mutual constraints

the interaction scheme of Figure 5.5. Achievement of their collaboration depends on the respective interpretations about the other's judgment policy.

Bilateral information channels are necessary to be shared between the operator and the autonomy, through which they can exchange their exploratory acts to each other with dense or enriched interaction cycles practicable. In Kirlik's words, they should share [PP,PA] variables as their commonly accessible media. In order to embed such functionality into the system, the author proposes to add mutual constraints of their respective actions depending on the other's behavioral conditions. Figure 5.6 provides a picture of this scheme, in which [PP,PA] variables for the respective autonomies are mutually constrained by some linkages (the region enclosed by a broken line in the center of the figure). Those embedded constraints bind the operator's operational acts with the autonomy's operational acts, and *vice versa.* They make the exploratory interaction cycles more compact while the two autonomies can virtually share their [PP,PA] variables. In this scheme, the robotic behaviors eventually reflect the interaction dynamics on the mutual constraints both of them attend to. Therefore, the authority to control over the robot may dynamically shift between the autonomies according to the relative strength of their contributing actions, which configure their mixed-initiative interactions. The constraints introduced here will function as the *shared communicational modalities* for human-machine collaboration.

5.4 Embodiment of Shared Communicational Modality in Tele-operation Environment

An experimental tele-operation environment has been developed to evaluate the proposed model of shared communicational modality, in which the control of a teleoperator robot is shared between a human operator and a robot autonomy. This section presents the experimental settings including the implementation of the shared communicational modality.

5.4.1 System Configuration

In the tele-operation system developed, a human operator operates a mobile robot (ActivMedia PIONEER1 Mobile Robot) in remote corridor environments by a joystick on a terminal PC which is connected with the robot through radio modems. The ambulatory motions of the robot are controlled by the translational and rotational velocities designated in response to the joystick position; forward-backward and right-left inputs to the stick are translated to the robot's behaviors of translational and rotational velocities, respectively. The robot has a CCD camera capable of panning, tilting and zooming (i.e., a robotic PTZ camera) on its front, and seven super sonic range sensors to measure distances from obstacles. The operators basically comprehend the surroundings of the remote robot using the real image from the camera. Figure 5.7 shows the display information available to the operators, which is composed of three different windows: (A) a real-image display from the remote camera, (B) a composite display representing the current state of the potential field for the autonomous obstacle-avoidance behavior described later, and (C) another composite display illustrating other status parameters such as the visual range of the camera, the measurements of the range sensors, and the movement speed of the robot. It is, however, difficult for them to understand the environmental state around the robot completely because of a large blind spot the camera has. As a mechanical support for this difficulty, a *obstacle-avoidance* behavior is equipped into the robot as its autonomy.

5.4.2 Robot Autonomy with Obstacle-Avoidance Behavior

The autonomy's obstacle-avoidance behavior is realized after a potential field method composed of repulsive forces from obstacles that are caught by the range sensors as illustrated in Figure 5.8. The *velocity* and *steering* commands to the robot are computed as below:

$$F_{R_i} = e^{-C_i d_i}, \tag{5.1}$$

$$velocity_{autonomy} = V_{MAX} \sum_{i}^{7} F_{R_i} \cos\theta_i, \tag{5.2}$$

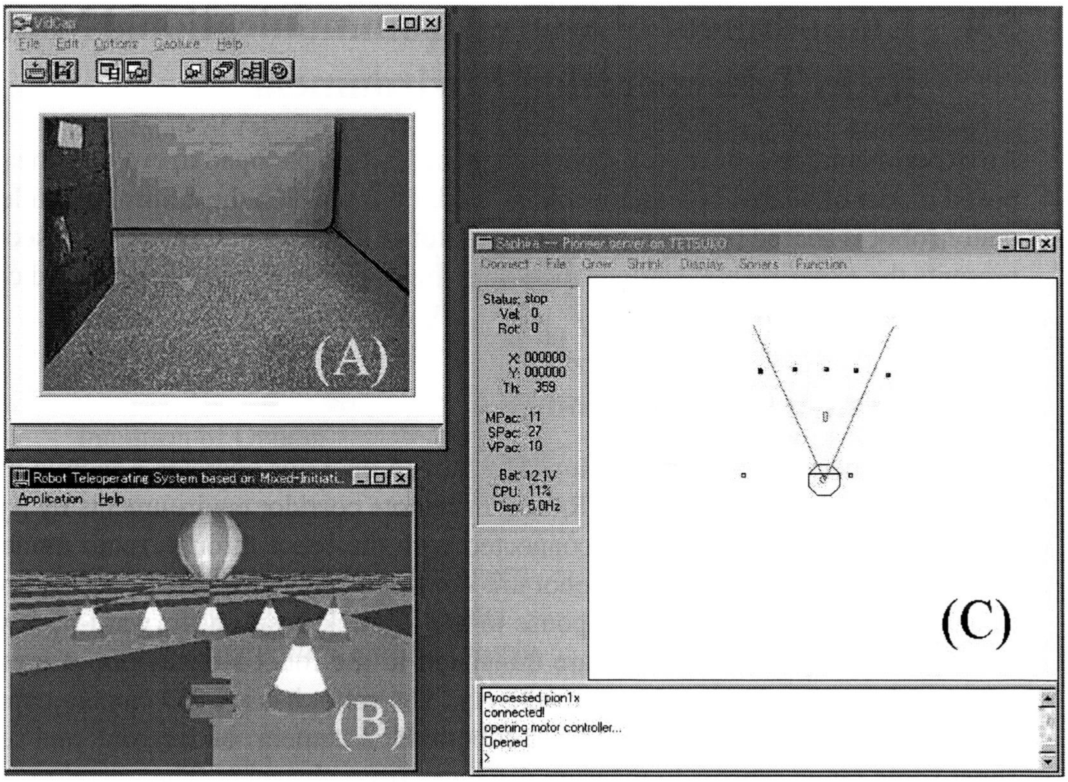


Figure 5.7: Screen shot of the display information

$$steering_{autonomy} = S_{MAX} \sum_{i}^{7} F_{R_i} \sin \theta_i. \tag{5.3}$$

Where, the parameter d_i indicates the distance measurement by the sensor $i \in \{1, 2, \ldots, 7\}$ whose direction angle is set to θ_i relative to the robot's heading. F_{R_i} is the intermediate variable which represents the magnitude of the repulsive force from the obstacle the sensor i has identified. C_i is the variable gain parameter of the potential field, which determines the strength of the sensor i's contribution. V_{MAX} and S_{MAX} are constants to translate the virtual forces into the ambulatory motion commands, and they are defined as $V_{MAX} = 300$ mm/sec and $S_{MAX} = 20$ deg/sec in tune with the specifications of the robot, respectively.

As this potential field has the parameters each of which determines the incline of the cone representing the effect of a particular obstacle, i.e. C_is, the autonomy can change its behavioral strategy by adjusting those parameters: if F_{R_I} gives a good effect upon the robot's behavior (e.g., the autonomy's decision has agreed with the operator's), the value of C_I is decreased to intensify the sensor i's contribution; but it is increased otherwise. The following equations define these update rules of each C_i value, actually implemented into the robot autonomy in both conditions with and

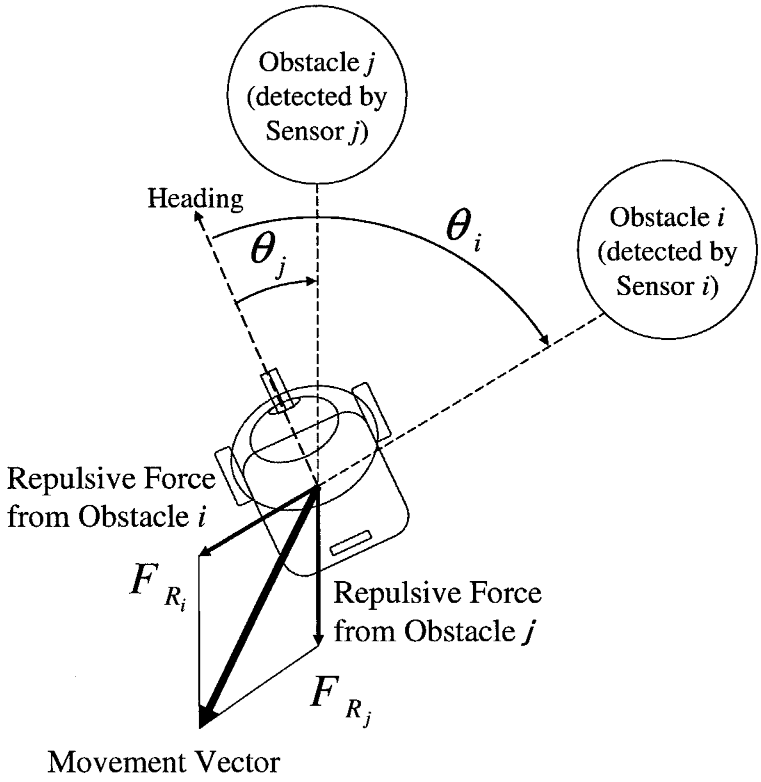


Figure 5.8: Potential field method to generate the ambulatory motion commands of the robot

without shared communicational modality:

$$C_i(t+1) = C_i(t) - \eta \Delta C_i(t), \tag{5.4}$$

$$\Delta C_i(t) = \Big(\sum_{j=\{velocity,steering\}} \sigma_j D_j R_{j,i} \Big) \times C_i(t). \tag{5.5}$$

Where, $\sigma_{velocity}$ (or $\sigma_{steering}$) is a flag whose value is $+1$ when the adjacent velocity (or steering) command by the autonomy has pointed the same direction with the human operator's, or -1 otherwise. D_j defines the difference between the actually commanded motion and the autonomy's command by the V_{MAX} or S_{MAX} value to get the relative strength of the human operation, in terms of either velocity or steering operation ($j \in \{velocity, steering\}$). $R_{j,i}$ indicates the sensor i's percentage contribution to the previous autonomy's decision on the translational or rotational operation. Finally, η defines the extent to which the next C_i will reflect the amount of modification derived from the difference between the human and the autonomy's commands, whose value was fixed to 0.01 of all the experiences. At the same time, the range of each C_i value is limited from 0.02 to 0.06.

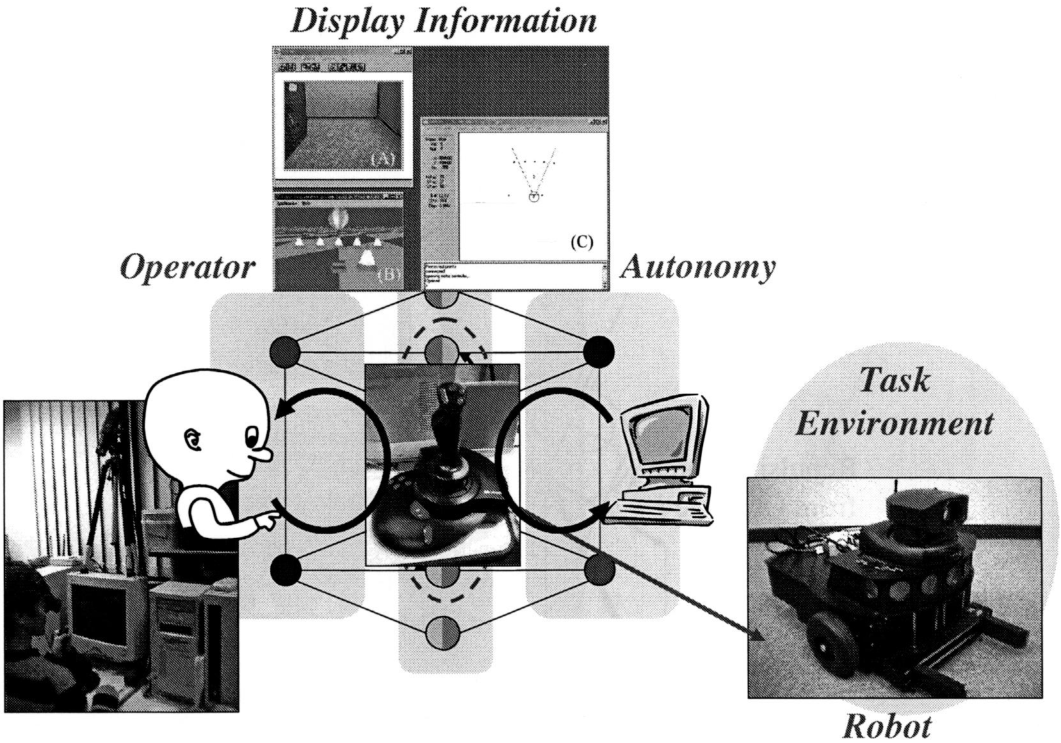


Figure 5.9: Implementation of shared communicational modality by a force-feedback joystick

5.4.3 Implementation of Shared Communicational Modality

The joystick with the mechanism to generate the force-feedback effect is used to "embody" the model of the shared communicational modality. By letting decisions of the autonomous obstacle-avoidance behavior reflect on the joystick motions using the feedback force, the autonomy can also manipulate the joystick as well as the operator. Therefore, the operator's and the autonomy's input actions are mutually restricted through the joystick, since both of them can manipulate it and affect the other's judgment policies. The initiative to control the robot can dynamically change according to the strength of their inputs to the joystick.

5.4.4 Experimental Settings

Figure 5.9 provides an overview of the developed shared-control system. Some experiments were performed to evaluate the effects of the proposed model. For comparison, another experimental setting was prepared without the force-feedback effects of the joystick. In this condition, the system displays the autonomy's decisions, i.e., velocity and steering commands from the potential field, on the window (C) in Figure 5.7, but the operator cannot manipulate its status directly. The latter condition is labeled as No-MII while the former condition of the proposed model as MII (the abbreviation for Mixed-Initiative Interaction). In both cases, the obstacle-avoidance behaviors of the robot autonomy had been informed to the operators before their experiments started. Finally, MAN represents the condition of the complete manual operation without any autonomy interventions.

5.5 Effects of Shared Communicational Modality

5.5.1 Performance Comparison

Table 5.2: Comparisons of average execution time in the zigzag corridor environment

	MAN	No-MII	MII
exec time [sec]	70.95	75.49	56.35

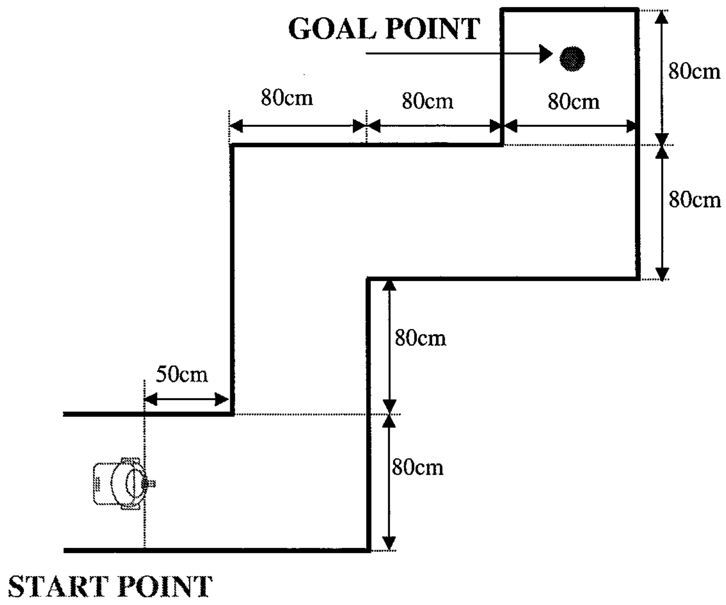
The first experiment was performed using the "zigzag" corridor shown in Figure 5.10(a). Three different operators performed a set of trials of MAN, No-MII, and MII experimental conditions by turns, and then repeated this set five times. As the result of this experiment, Table 5.2 summarizes the average values of execution time for the three different experimental settings, indicating better performance of the MII collaboration style than the others.

In order to investigate its cause from the perspective of the Lens Model framework, another experiment was performed using the "L-formed" corridor environment of Figure 5.10(b), which has narrower width to detect a small mistake of the robot handling as a collision with a wall. Its simple form contributes easy capturing of the operator's and the autonomy's judgment policies to control the robot. In this experiment, four different operators executed a set of trials of No-MII and MII conditions by turns until ten sets.

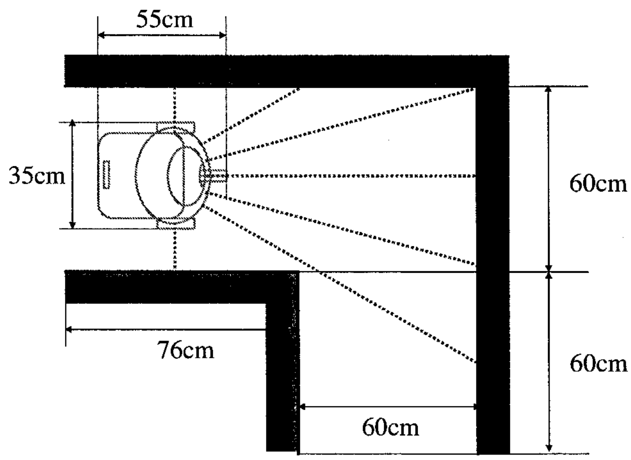
Table 5.3: Comparisons of some statistics between two different experimental conditions of No-MII and MII

	P_{suc}	$\bar{T}$ [sec]	$\bar{T}_S$ [sec]	$\bar{T}_F$ [sec]	$\bar{N}_{cw}$
No-MII	0.425	14.3	12.7	**18.4**	1.52
MII	0.625	13.6	12.6	**15.5**	1.4

Figure 5.11 shows profiles of task completion time obtained from this experiments, comparing them between No-MII and MII task conditions. Comparison of the profiles between the two different conditions indicates that operations in the MII condition exhibit more equable performances all through the trials than in the NO-MII condition. In the latter case, larger amount of fluctuations is observed between

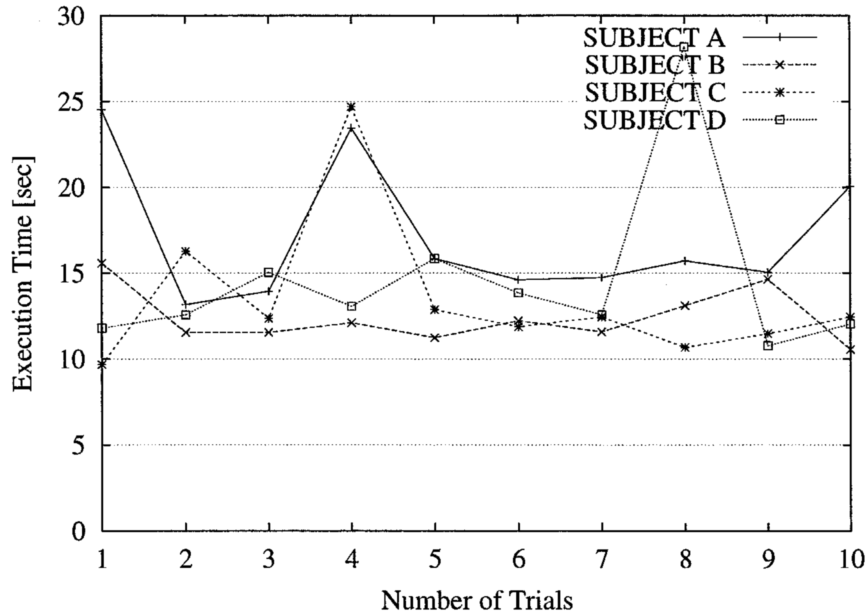


(a) *Zigzag* type

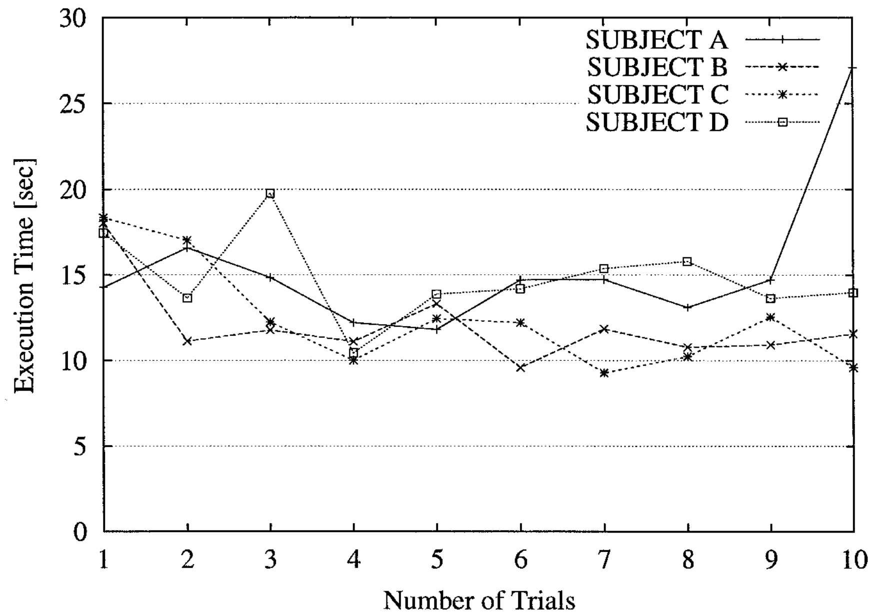


(b) *L-formed* type

Figure 5.10: Two corridor environments for experiments



(a) No-MII condition



(b) MII condition

Figure 5.11: Profiles of execution time in the *L-formed* corridor environment

successful and *unsuccessful* trials. Here, successful trials represent the runs during which the robot had no collisions with walls and thus no "cut-the-wheel" operations to back in the course were made. Concerning this result, Table 5.3 compares some statistic values computed from the data recorded in the trials. Wherein, P_{suc} and $\bar{T}$ represent the success rate of the navigation task (i.e., with no collisions) and the averaged task completion time all through the trials in each condition, respectively. $\bar{T}_S$ is the average value of task completion time among the successful trials as well as $\bar{T}_F$ among the unsuccessful trials. $\bar{N}_{cw}$ represents the average number of cut-the-wheel operations among unsuccessful trials. While MII basically outperformed No-MII about all these statistics, $\bar{T}_F$ is the most noteworthy variable to distinguish between No-MII and MII. It suggests that operations in the No-MII condition took longer about recoveries from collisions than in the MII condition. This result can be thought of as follows: the autonomy's "indirect" interventions into human decisions may work well while their joint activity is going smoothly; but otherwise it may cause some mismatch between the robot's actual behavior and the operator's anticipation on it, confusing human judgments. At the same time, the unified action modality through the mutual constraint embedded seems to contribute to the adjustments of human and mechanized decisions during recovery operations when they are easy to deviate from a coordinated relation to a conflicting one, especially.

Coordinated collaboration by independent autonomies involves the adequate role-assignment among them; each contributor should occupy its own "niche" from the social perspective of their joint activity. The socially epistemic actions compose the sustained efforts to find out their positions. The author would like to contemplate the different behaviors between the two collaboration styles explained above from this point of view. Therefore, to examine the social relationship between human and mechanized decisions, the Lens Model formalism is deployed in consideration of its parallel indices as well as its policy capturing methodology.

5.5.2 Depiction of Judgment Policies Based on the Lens Model Formalism

The human-machine joint judgment structure in the cooperative tele-operation environment is depicted based on the Lens Model formalism. Figure 5.12 illustrates the criterion-judgment model obtained from the analysis. On the one hand, the operator's and the autonomy's judgments, denoted as Y_{OP} and Y_{AT} respectively, contribute to the locomotion control of the teleoperator robot as they are jointed into the judgment of Y_J in this model. Y_J provides the actual *velocity* and *steering* commands to the robot. Both judgments of Y_{OP} and Y_{AT} are rendered on the basis of available cues. As the cues composing the model, the following state variables

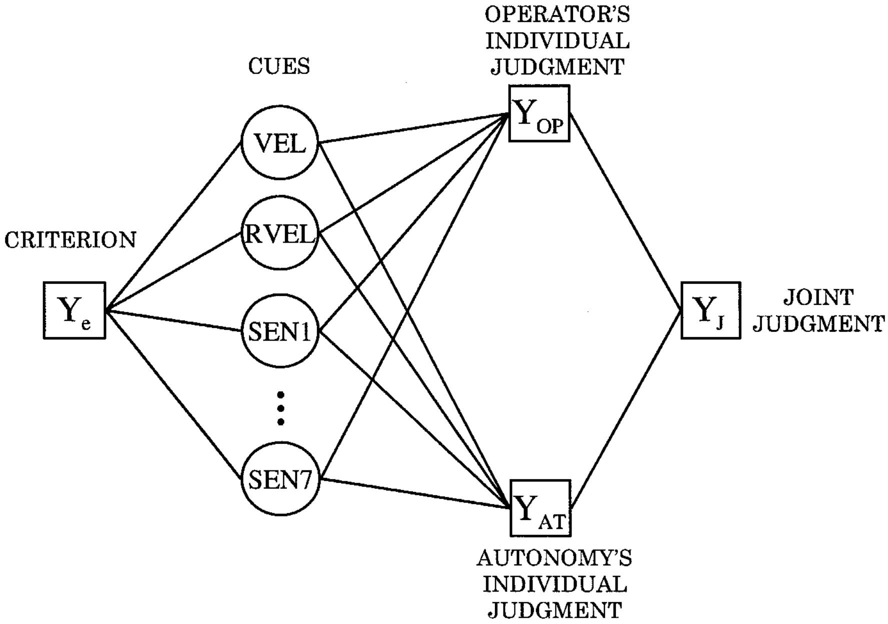


Figure 5.12: Depiction of the human-machine joint judgment scheme in terms of the Lens Model formalism

are selected because of their measurability[1]; the robot's translational (VEL) and rotational (RVEL) velocities, and the measurements of all range sensors (i.e., SEN1, SEN2, ..., SEN7). The connections among those cue variables and each judgment indicate the judgment policy, or decision structure, attributed to the human or machine autonomy. On the other hand, Y_e represents the criterion of the robot operations, i.e., the counterpart of Y_J. In the tele-operation task analyzed in this chapter, however, the actual criterion values are not available because the ideal operation in each situation cannot be determined. Instead, the parallel data set recorded during much skilled operations was utilized to extract the criterion model $\hat{Y}_e$.

Based upon this modeling scheme, the respective judgment strategies were captured as their policies, i.e., $\hat{Y}_{OP}$ and $\hat{Y}_{AT}$. Multiple regression modeling [9] is the most prevailing in policy capturing methodologies [6] and therefore it was employed here as well. By applying this method to the parallel data set of cue values and judgments, models of each operator's or autonomy's judgment strategies were generated as linear combinations of the cues (i.e., these cues are regarded as independent or predictor variables to explain each judgment as a dependent or criterion variable). Specifically, utilization of each cue is expressed as the correlation

[1]As mentioned in section 5.4.1, human operators basically comprehend the surroundings of the remote robot based upon the live video images sent from the on-board camera. It is, however, difficult to quantify the states given by the images, and thus they are substituted for by the range sensor measurements as their approximate values in this analysis.

between that cue value and the judgment, and $\hat{Y}_{OP}$ and $\hat{Y}_{AT}$ take the form of the weighted sum of cue variables as bellow:

$$\hat{Y} = b + b_{VEL}X_{VEL} + b_{RVEL}X_{RVEL} + b_{SEN1}X_{SEN1} + \ldots + b_{SEN7}X_{SEN7}. \qquad (5.6)$$

For each operator, his own and the autonomy's judgments on the locomotion control (i.e., both *velocity* and *steering* operations) as well as the cue values were sampled every 500 msec during a run for inclusion in their respective models. The records in the recovery periods after the robot had collided were cut out from the data set used to create the models[2]. *Stepwise model-building technique*[3] was employed for regressing judgment policies, in which a critical F value as the stepping criterion was specified to 2.0.

5.5.3 Analyzing Control Competency in Human Judgments

After capturing the judgment policies from behavioral data of the second experiment, several statistic indices in relation to the Lens models were calculated. This section particularly takes notice of human judgments, i.e., Y_{OP}'s, considering how the different collaboration styles affected modifications of their policies and eventually their collaboration performances as experiences of the joint activities enlarge. For this purpose, the correlations were analyzed between the Lens Model statistics values and two performance measurements, that is, the task completion time T and the number of cut-the-wheel operations N_{cw}.

Table 5.4: Averaged correlation coefficients between the RMS errors from the captured human judgment policies and the task completion time T

	No-MII	MII
velocity	0.349	0.205
steering	**0.652**	**0.837**

The analysis result indicates that the *residual mean square* (RMS) errors [9] from the judgment models of the steering operations score high on the correlation coefficients with the performance measurements. The RMS error is a measure of

[2]The reasons for this data processing are following: to lump "cut-the-wheel" operations together with regular ones makes accuracy of the judgment models much worse; and enough size of data in those periods cannot be assured to generate the models of the recovery operations only, in addition to the regular ones.

[3]The basic procedures of the stepwise model-building techniques involve (1) identifying an initial model, (2) iteratively "stepping", that is, repeatedly altering the model at the previous step by adding or removing a predictor variable in accordance with the "stepping criteria", and (3) terminating the search when stepping is no longer possible given the stepping criteria, or when a specified maximum number of steps has been reached. Critical F values are one type of the stepping criteria that can be used to control entry and removal of effects from the model.

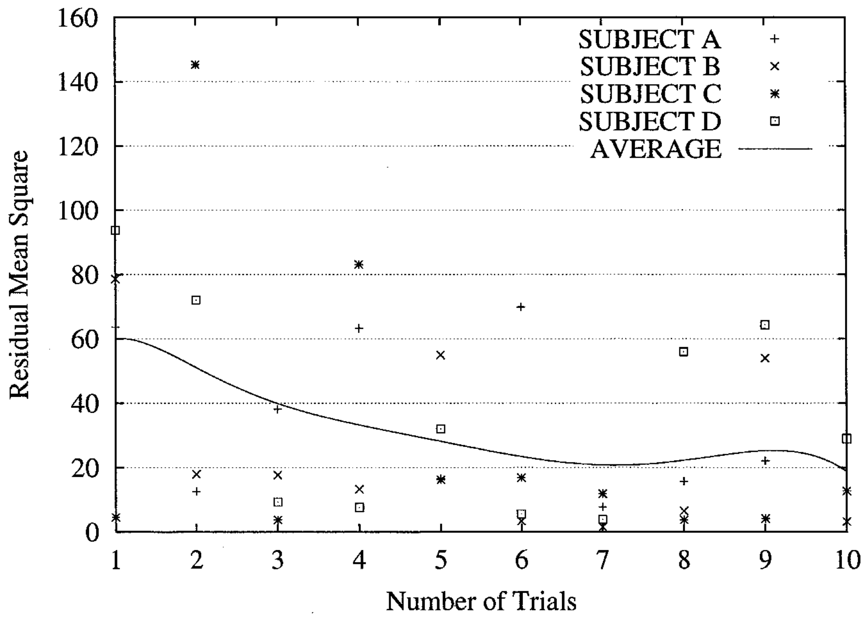
Table 5.5: Averaged correlation coefficients between the RMS errors from the captured human judgment policies and the number of cut-the-wheel operations N_{cw}

	No-MII	MII
velocity	0.617	0.298
steering	**0.702**	**0.547**

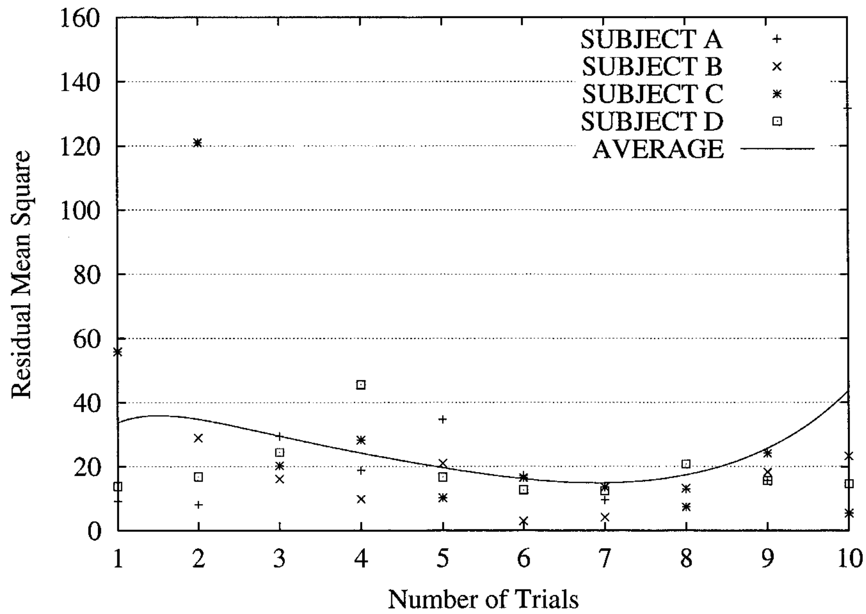
how poorly a regression line (i.e., a captured judgment policy) fits actual data points (i.e., actual judgments), given by $\{\sum_{i=1}^{n}(\mathrm{Y}_{\mathrm{OP_i}} - \hat{\mathrm{Y}}_{\mathrm{OP_i}})^2\}/(n-2)$ where the number n is the sample size. Table 5.4 and 5.5 present the averaged correlation coefficients of those RMS errors from both velocity and steering judgment models with the values of T and N_{cw}, respectively. These comparisons prove that the operational skills with the less RMS errors in terms of the steering operations demonstrated higher collaboration performances, i.e., shorter completion time and less cut-the-wheel operations.

Errors from regression models contain both unsystematic random errors and systematic but unmodeled influences. On the latter aspect, the possible factors to magnify the RMS errors would involve inconsistency and/or uncontrollability in the individual's judgment process as well as misspecifications of the policy models. If relevant cues which the subject actually uses to help inform his/her judgments are omitted, or if some configural (or nonlinear) cue usage occurs in his/her policy, it will increase variability in judgments that is not explained by the policy model. At the same time, if the individual judge has not acquired self-control competencies for rendering consistent judgments, identical cue information is processed and integrated to produce differing judgments. In such cases, the variance between actual judgments and predictions by the model is enlarged because any statistical models will generate the same predicted judgment on all occasions with the same set of cue values. Regardless of the experimental conditions of No-MII and MII, variations of the RMS errors were observed in the *same* modeling scheme, i.e., the same cue selections for regression, and thus fluctuations in their comparisons can be assumed to be derived from judgment competencies. The analysis here is concerned only with this point of view, where the RMS errors from the policy models of the steering operations are employed as the index of the operator's competencies.

Figure 5.13 compares several profiles of the RMS errors from the human policy models on steering operations along the number of trials. As a general trend, we can see that the profiles under the MII condition demonstrate more equable transitions with smaller errors than the cases of the No-MII condition. These behaviors can be considered, from the perspective mentioned above, as that the operators in the MII collaboration style could appropriately control their judgments in the joint operations with the robot autonomy. The distributed errors observed in the No-MII condition contrary suggest that such control in their judgments might be disturbed. It is estimated that "quiet" interventions by the autonomy might confuse human op-



(a) No-MII condition



(b) MII condition

Figure 5.13: Profiles of the RMS errors from the human policy models on steering operations along the number of trials

erations (probably in the nearly failure situations, on the ground of the discussions in section 5.5.1), which implies that the adequate role-assignment had not been established between human and machine autonomies. Meanwhile, we can also see the downward trend of the RMS errors in the No-MII condition (Figure 5.13(a)), which reminds us of gradual but steady acquisition of more suitable judgment policies to work with the autonomy as experiences of the joint activities accumulate. In the light of these findings, the disparity between the collaboration styles comes in how effectively they can contribute to cultivation of more cooperative human-machine relationship, or their better partnership.

5.5.4 Analyzing Relational Modification Process between Judgment Policies

Based upon the resulting prospect on the human-robot collaboration styles contributing to acquisition of their better partnership, here is focused on the relative relation between human and mechanical judgment policies. So as to examine their relation, the distance between their captured policy models, i.e., $\hat{Y}_{OP}$ and $\hat{Y}_{AT}$, was utilized as the approximate indexical measurement representing how different or how similar the two policies are. More specifically, the *Euclidean distance* between the cue weight profiles, or the sets of regression coefficients, of the two policy models was employed to measure that relationship. In this approach, however, measurement scale effects between cues must be removed from the magnitude of regression coefficients because cue variables with smaller domains will have much influence on the distance measurement otherwise. For this reason, standardized regression coefficients (β weights) were used to compose a cue weight profile, which are calculated by converting scores on each cue to standard scores that always have a mean of 0 and a standard deviation of 1.0.

Equation 5.7 defines the distance between $\hat{Y}_{OP}$ and $\hat{Y}_{AT}$ used in the analysis later, in which $\beta^{(j)}_{OP,i}$ and $\beta^{(j)}_{AT,i}$ represent each standardized regression coefficients of the human and mechanical judgment policy models respectively. This measurement includes both aspects of velocity and steering control, and thus the parameter j is defined as $j \in \{velocity, steering\}$. The parameter i indicates every cue variable implicated in the regression models, that is, $i \in \{\mathrm{VEL}, \mathrm{RVEL}, \mathrm{SEN1}, \ldots, \mathrm{SEN7}\}$.

$$distance_{\hat{Y}_{OP}-\hat{Y}_{AT}} = \sqrt{\sum_j \sum_i (\beta^{(j)}_{OP,i} - \beta^{(j)}_{AT,i})^2}. \tag{5.7}$$

Figure 5.14 parallelizes the averaged values of $distance_{\hat{Y}_{OP}-\hat{Y}_{AT}}$ between the No-MII and MII conditions for each subject. From this chart, we can easily understand that the human operators under the No-MII condition evidently made more similar judgments with the autonomy's than the case of the MII condition. Similarity between the judgment policies implies that redundant or at least partly overlapped

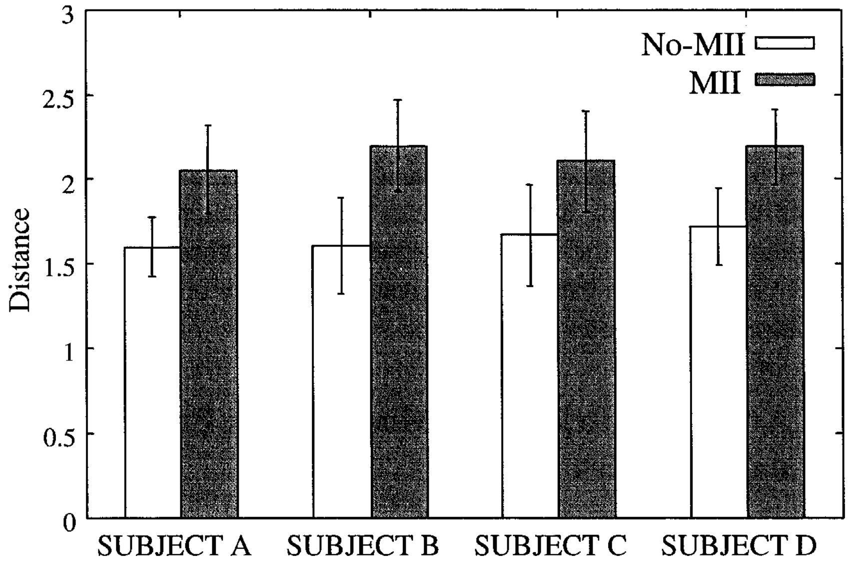


Figure 5.14: Comparisons of the averaged value of $distance_{\hat{Y}_{OP}-\hat{Y}_{AT}}$ between No-MII and MII for each subject

operations by the two different autonomies may occur. Those operations increase the likelihood that extra or excessive control inputs may come into effect on the robotic behaviors than anticipated from the operator's point of view, especially in the case where he/she has not worked out the nature of the autonomy's judgments. Such unestablished states of task-sharing will bring about inconsistency or uncontrollability in human judgments. Another independent entity might introduce some "noises" into the system and should so hinder the operator's adequate reactions to their work situations.

On the other hand, even under the No-MII condition, gradual modifications of the human-machine relationship were confirmed in terms of their $distance_{\hat{Y}_{OP}-\hat{Y}_{AT}}$ measurements. Table 5.6 compares those values between early (averaged among the first three trials) and final runs (averaged among the last three trials) for the respective operators under the two collaboration styles, appending their percentage increases. All the results here indicate those behaviors of enlarging distance between $\hat{Y}_{OP}$ and $\hat{Y}_{AT}$, without reference to differences among individuals and between the collaboration styles. They tell us that accumulated experiences of the joint activities differentiated their roles to contribute to the robotic control, and that consequently they could, in some senses, cultivated a complementary relationship with each other. At the same time, the $distance_{\hat{Y}_{OP}-\hat{Y}_{AT}}$ measurements in the MII collaboration style are considerably large even from an early stage (see Table 5.6(b)), supporting the perspective on more swift development of good human-machine partnership through the shared communicational modality.

Table 5.6: Comparisons of $distance_{\hat{Y}_{OP}-\hat{Y}_{AT}}$ values between early and final runs

	Early Runs (AVG. of 1-3)	Final Runs (AVG. of 8-10)	Percentage increases
SUBJECT A	1.610	1.617	+0.5%
SUBJECT B	1.380	1.707	+23.7%
SUBJECT C	1.526	1.928	+26.3%
SUBJECT D	1.546	1.708	+10.4%

(a) No-MII

	Early Runs (AVG. of 1-3)	Final Runs (AVG. of 8-10)	Percentage increases
SUBJECT A	2.018	2.080	+3.1%
SUBJECT B	2.019	2.308	+14.3%
SUBJECT C	2.130	2.222	+4.4%
SUBJECT D	2.195	2.217	+1.0%

(b) MII

5.6 Discussions

After the intimate analysis of the human-machine joint activity based upon the RMS errors and the distance measurements between the individual policy models, it was reasoned that the human operators had become to understand the nature of the autonomy's judgment policy through their practical work experiences as well as the autonomy had gotten to accommodate to individual operational skills in turn. Their respective roles in the shared control of the robot had eventually changed into better assignments from the initial ones. Meanwhile, the disparity in their performance between the collaboration styles with (MII) and without *shared communicational modalities* (No-MII), comes in how effectively they can contribute to cultivation of more cooperative human-machine relationship. The experimental results proved that their good partnership could be more swiftly developed with the shared modalities. Collaborations by independent autonomies, in principle, demand common information resources to facilitate establishing coherent and consistent judgments among them. Herein, the shared communicational modality is expected to play such resources toward their dynamic and fluent interactions. So as to formally explain the modality's function from this perspective, the former depiction of the human-machine joint judgment (i.e., Figure 5.12) is expanded.

Figure 5.15 presents the expanded view of the human-machine joint judgment where the individual policy modification processes are added to the original one.

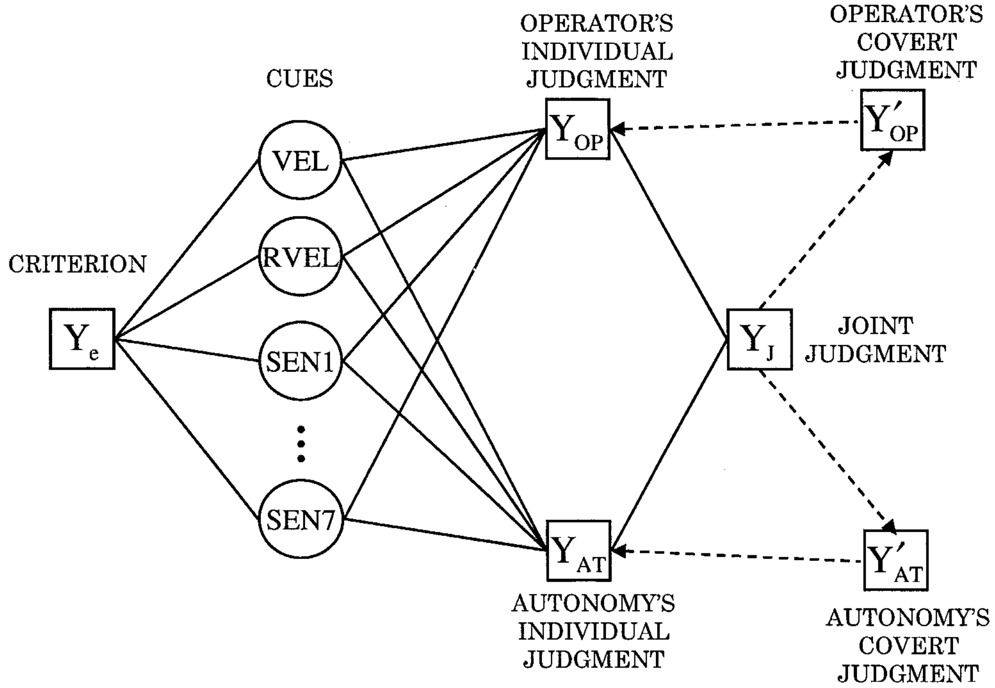


Figure 5.15: Policy modification cycles via the joint judgment

As has been previously described, the actual robotic behaviors are controlled by the judgment Y_J which is composed of the two autonomies' judgments of Y_{OP} and Y_{AT}. In terms of adjustments or revisions of the judgment policies here, some *covert judgments* [6] are assumable that try to move one's judgment toward the compromise position as reflecting the influence of the other's policy. The expanded model depicts two covert judgments of the human operator and the robot autonomy as Y'_{OP} and Y'_{AT}, respectively. The operator's introspecting process is represented by the directed broken lines going through Y'_{OP}, where his/her judgment policy Y_{OP} can be adjusted as considering its relative location to the partner's policy Y_{AT} through their joint judgment Y_J. Altogether, Y'_{OP} plays kind of *meta-level* cognition in the operator, which organize Y_{OP} on the basis of the Y_{OP}-Y_{AT} relationships. The same applies to the case of the robot autonomy.

In this view of the joint cognitive system, Y_J plays a significant role for improvements of the human-machine interaction because it does mediate and influence both modification cycles of the human and mechanical judgment policies. Concerning their better partnership emerging from those cycles, the point is the accessibility to the joint judgment for each judge. In the MII collaboration style, the human operators can directly assess the state of Y_J through the embodiment of the shared communicational modality as shown in Figure 5.16. Moreover, the modality also allows their direct manipulation of the state of Y_J. That is to say, the shared com-

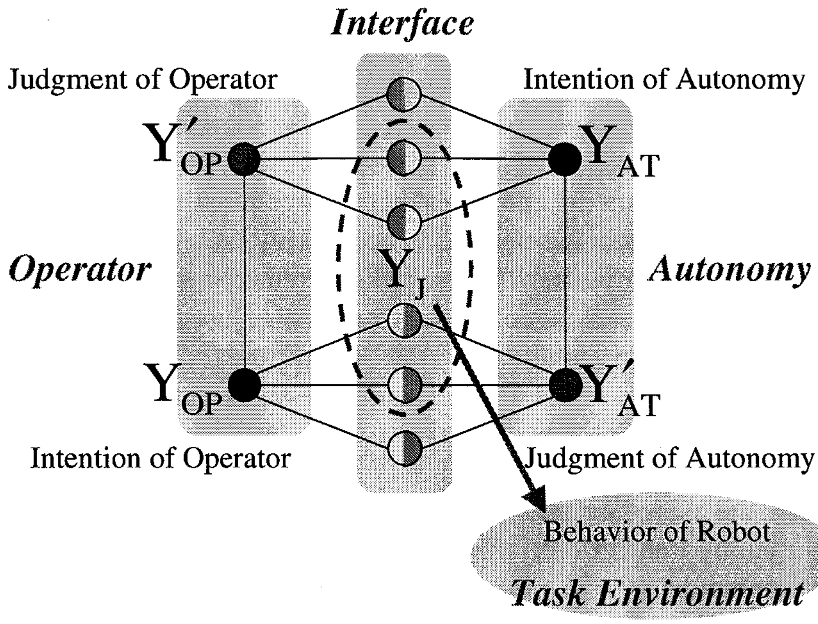


Figure 5.16: Relations among five different judgments in the proposed collaboration scheme

municational modality provides direct access to the joint judgment from *both* perspectives of perception and action. Coupling the respective [PP,PA] variables with each other brings together those proximal resources the subject can act to and get feedback from. From the viewpoint of *epistemic actions* to improve cognition, this functionality will effectively contribute to the explorations of the appropriate cooperative relationship in the human-machine system. On the other hand, the No-MII collaboration style provides no such resources. Those what the operators can act to and get feedback from are completely separated as the interaction loop shown in Figure 5.5. These estimated accounts portray the capability of the shared communicational modalities and then resulting collaboration performances different between with and without them.

5.7 Summary

This chapter provided a formal approach to designing effective human-machine interaction channels between a human operator and a machine autonomy in their shared-control situations. At first, after the qualitative classification of information types defined in Kirlik's *Generalized Lens Model* framework, variables in that human-machine system were distinguished in terms of "proximal or distal" from the both perspectives of perception and action for each decision-maker, as well as their latent covariant relations were depictured.

Secondly, based upon the fundamental philosophy that any collaborative human-machine systems need to accommodate human and machine-autonomy's variable actions including their *epistemic actions*, a new human-robot collaboration style has been proposed with the *shared communicational modality* between them. The proposed interaction model embodies their communicational modality by imposing the mutual constraints between their respective [PP,PA] (i.e., proximal for both perception and action) variables. This embedded connection between the two decision-makers can increase each agent's opportunity to adjust their operational strategies to the other's behavior, and thus promotes their mixed-initiative interactions.

Finally, according to this guiding principle, an experimental shared-control environment composed of a human operator and an autonomous mobile robot was developed, in which a joystick with the force-feedback effect generator is utilized to embody the shared communicational modality. By letting the intentions of the robot autonomy transfer onto the joystick using the feedback force, the autonomy can also manipulate the joystick as well as the operator. Thus, the operator's and the autonomy's input actions are mutually restricted through that joystick, since both of them can manipulate it and affect the other's judgment policies. This actual experimental environment was used to verify the shared communicational modality providing with the direct access to the significant property of their joint judgment for adequate revisions of their individual judgment policies and their adequate role-assignments.

Chapter 6

Design of Probing Behaviors for Adaptation of Machine Autonomy

6.1 Introduction

Mechanized control has advantages over human control such as tireless vigilance, increased precision, and fast processing, while human control has also advantages over mechanized control such as the ability of comprehensive situation awareness and assessment, and the flexibility to cope with unfamiliar or unprogrammed situations by utilizing a various kind of knowledge. Hence, it is an important challenge in the human-machine systems design to combine and capitalize on both advantages of human and mechanized automatic controls. Concerning this challenge, there proposed the ideas known as "shared control" [47,48] and "shared autonomy" [18], as the concepts for human-machine collaboration designs to provide the reciprocal complementarities after their "joint activity". Herein, the joint activity represents the integration of individual decisions made in parallel by two or more different and independent agents including humans and machines, and especially shared autonomy stresses that they should collaborate with one another as *equivalent* partners (see section 5.1 for more detail).

Because of essential differences in physical and cognitive capabilities between humans and machines, it is conceivable to combine their individual decisions complementarily. In their combination, those differences will provide different accesses to an identical task situation, which can contribute to enhancing overall performance of the system. However, any interventions by other than his/her own decisions may become factors disordering human operations. Interventions by the machine autonomy could hurt the system's operationality for the operator by introducing unexpected behaviors into the system. As mentioned in section 1.2.2, all efforts to resolve such mismatch between humans and machines are charged only to the human operators (namely, to human adaptation). Machines only execute what they are programmed to do close-mindedly, and so have no ability to deal with and adapt to variable behaviors of their human partners. Thus, the more complex the decision structure of the machine autonomy, the harder it is for the human operators to accommodate themselves to such a system.

From this perspective, some flexibility and adaptability with humans are to be developed in those mechanical systems toward the truly collaborative partnership where humans and machines can operate harmoniously. Every machine autonomy is, in principle, working as an intermediary computational process between the human operators and the mechanical end effectors, and therefore has potentials enough to influence the human behaviors including their adaptation. Based upon this idea, here is proposed a new behavioral design concept for mechanical adaptation as focusing on and addressing necessary elements for the adequate human-machine coordination. Our humans proactively act on the external world not only to get physically closer to the goal but also to improve uncertain cognition about dynamic and not completely observable environment. Inspired by this sensible way of doing, the author advocates to introduce proactive agency into the machine autonomy so that it can probe or sound out the partner's *covert* judgments for its adaptation through their human-machine "dialogue". As the testbed environment of this scheme, a simulated shared-control environment has been developed, in which both a human operator and a machine autonomy can control the behavior of a mobile robot. Their collaboration work is experimented to analyze some aspects of the human-machine joint activity, especially, possible disorders between the operator and the autonomy due to their different cognitive natures. After this analysis, discussions are made about feasibility of the proposed approach toward the well-coordinated human-machine relationship by evaluating a demonstration of the mechanical adaptation.

6.2 Probing Behaviors for Adaptation

Figure 6.1 illustrates the diagram depicting the relations among three different interactive systems in a shared-control environment. Where, P_* and A_* indicate coupled interactive processes of perception and action respectively while I_* represents the intention that constrains the coupling of P_* and A_*. The interaction field configured by the human operator and the interface devices is labeled as Human-Interactive System (HIS) while the field between the mechanical front (i.e., sensors and actuators) and the objective task environment is defined as Task-Interactive System (TIS). In light of the "transparentized chain" in the human-machine system (see section 2.2), the height of human-machine collaboration can be regarded as supported by the adequate correspondence between HIS and TIS, by which intentions of the respective systems are transmitted to the other in the isomorphic fashion, in a sense. But as mentioned in the introductory section, it is infeasible to design

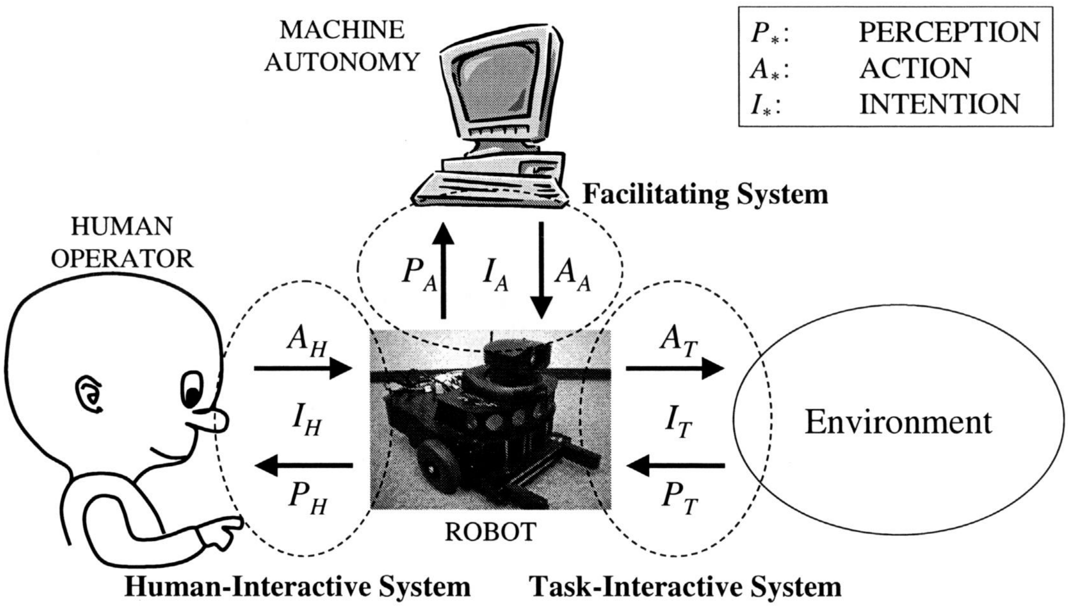


Figure 6.1: Depiction of the relations among the three interactive systems in a shared-control environment.

such a mapping by any *external* designers in advance. Rather, some self-regulating mechanism is necessary so that the system itself can constantly coordinate its internal communicative structure as considering the dynamics emerged from actual interactions among its subsystems. From this perspective, mechanical autonomies should be open to modification or revision for the sake of facilitation of the human-environment interactions they mediate. Their own behavioral adaptation will be performed not only to their task environments but also to their human partners. In this sense, the machine autonomy functions as Facilitating System (i.e., FS).

This duality of the adaptation targets, however, causes problems on the stability-plasticity balance in the machine autonomy. The autonomy has to maintain its independence and identity for their functional complementarity in the human-machine joint activity as well as comply with the demands for their coordinated relationship flexibly. For this end, the adaptive system must discriminate certain feedback information utilized for its adaptation from others for stable control toward a target state in terms of its original functionality [10]. In relation to that exploitation of feedbacks for adaptation purposes, proactive use of actions is fundamental. Our humans often proactively act on the external world to improve uncertain cognition. This exploratory or knowledge-granting aspect of action, called *epistemic action* [26, 28, 29], can contribute to making latent information overt by activating constraints which connect proximal cues and hidden or distal structures. Such behaviors will certainly create an opportunity for appreciating feedback information for adaptation in the collaborative systems, the author considers. In other words, the timing in which individual adaptations are conditioned is a critical parameter to coordinate their joint activity and thus strike the stability-plasticity balance in the adaptive systems.

At the same time, those exploratory acts invoke more frequent interactions among autonomies in the system, and thus they will help the one to know the hidden intent structures in the other's decision. Such interactions can encourage the autonomies to share their mutual understandings and judgmental consistency. This perspective is analogical with the problem-solving through dialogues in the nature of the mixed-initiative interaction [11, 12]. The participants in such interactions are powerfully driven by the motivation to reducing the uncertainties about the partner's intention [20]. This means nothing else that just the accumulated interactions among them can construct their common and mutual beliefs requisite for their true collaboration.

So as to give shape to the above discussion, the author advocates to introduce *proactive agency* into the machine autonomy so that it can probe or sound out the partner's covert judgments for its adaptation through their human-machine dialogues. This agency is motivated by decreasing uncertainties about the partner's behaviors, and it will be triggered by the possibility of discrepancy between the autonomy's anticipation and the actual operator's behavior. Through such proactive agency, the machine autonomy adapts its behaviors to their collaboration as retrieving more information about the partner's "varying and transient" decision structures.

6.3 Necessary Coordination within Human-Machine Shared Control

The first experiment was performed using a simulated shared-control environment in which human and machine autonomy's operations were simply superposed to the total system behavior. Its results were analyzed to discuss the effect of the human-machine joint activity, focusing especially on possible disorders between a human operator and a machine autonomy due to their difference in cognitive properties.

6.3.1 Experimental Settings

For the experiment, a simulated shared-control environment was prepared in which a virtual mobile robot was controlled by either or both of a human operator and a machine autonomy (i.e., the robot autonomy). The experimental task is that they collaboratively navigate the robot through the L-formed corridor presented in Figure 6.2. This virtual robot models after the actual ActivMedia PIONEER1 Mobile Robot, and thus has seven range sensors in front as well as a camera fixed onboard. The range sensors can measure the distances from the robot to the nearest obstacles

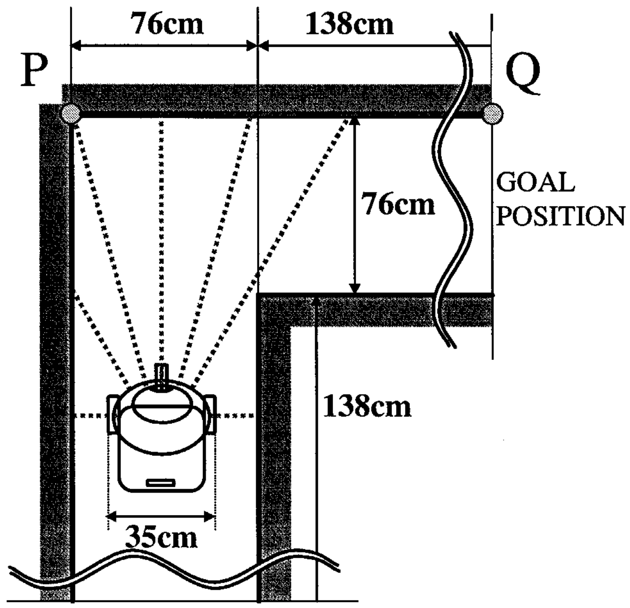


Figure 6.2: L-formed corridor environment for the simulated shared-control task

in the respective directions, whose measurements are utilized as the perceptual data to the machine autonomy as described later. The captured image by the camera is rendered onto the display window the human operators refer as their primary informational resource. As sensing the "remote" situation through the display, the human operators manipulate the robot by a joystick whose inclination determines the operational commands for the transitional and rotational velocity of the robot.

However, as shown in Figure 6.3, view of the camera is very restricted so that human operators have got little information on the body image and dynamics of the robot. The operators of this tele-operation environment have to develop the adequate models on the robot through their own experiences to achieve smoother and quicker task completions. In order to alleviate this difficulty, a simple obstacle-avoidance behavior is embedded into the robot as its autonomy, which is realized by the potential field method. The potential field is calculated from the measurements of the range sensors after the equation (6.1), (6.2), and (6.3) to generate the autonomy's operational commands:

$$F_{R_i} = e^{-C_i d_i}, \tag{6.1}$$

$$velocity_{autonomy} = V_{MAX} \sum_{i=1}^{7} \omega_i F_{R_i} \cos\theta_i, \tag{6.2}$$

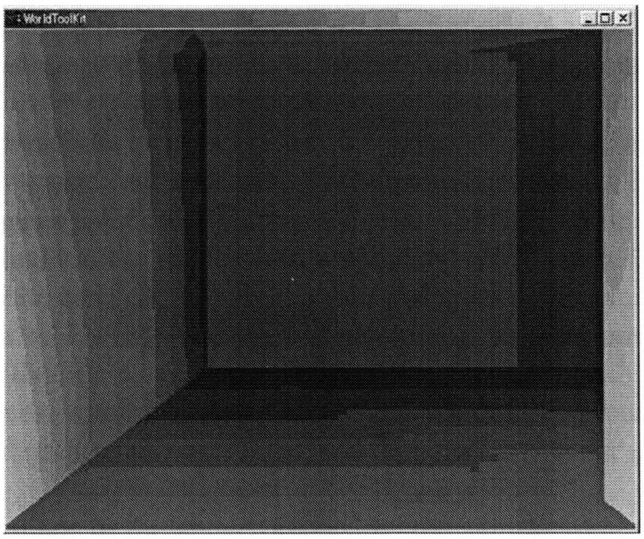


Figure 6.3: Viewport image from the onboard camera

$$steering_{autonomy} = S_{MAX} \sum_{i=1}^{7} \omega_i F_{R_i} \sin\theta_i. \tag{6.3}$$

Where, the autonomy's operational commands for the transitional and rotational velocity are denoted as $velocity_{autonomy}$ and $steering_{autonomy}$, respectively. The parameter d_i represents the distance measurements by the sensor $i \in \{1, 2, \ldots, 7\}$ whose direction angle is set to θ_i relative to the robot's heading. F_{R_i} is an intermediate variable representing the magnitude of the repulsive force from the obstacle the sensor i has identified. C_i indicates a variable gain parameter of the potential field, which determines the strength of the sensor i's contribution, and thus the autonomy can change the way to generate its potential field by adjusting the values of C_is. On the other hand, V_{MAX}, S_{MAX} and ω_i are constants which should be tuned for good performance of the isolated autonomous behaviors. Figure 6.4 illustrates the way to realize this autonomous obstacle-avoidance behavior.

6.3.2 Different Cue-utilization Styles between Human and Machine Autonomies

Examining the effects of the machine autonomy's intervention into human control was carried out based on comparisons between the human operations with and without the autonomous obstacle-avoidance behavior. For this purpose, eight experimental subjects (i.e., subject A, B, ..., H) at first executed the tele-operation task with no assistance by the autonomy, and each of them performed 10 experimental trials in this experiment. Those results reveal one typical feature of the human control in this tele-operation; humans basically make *continuous* judgments on their

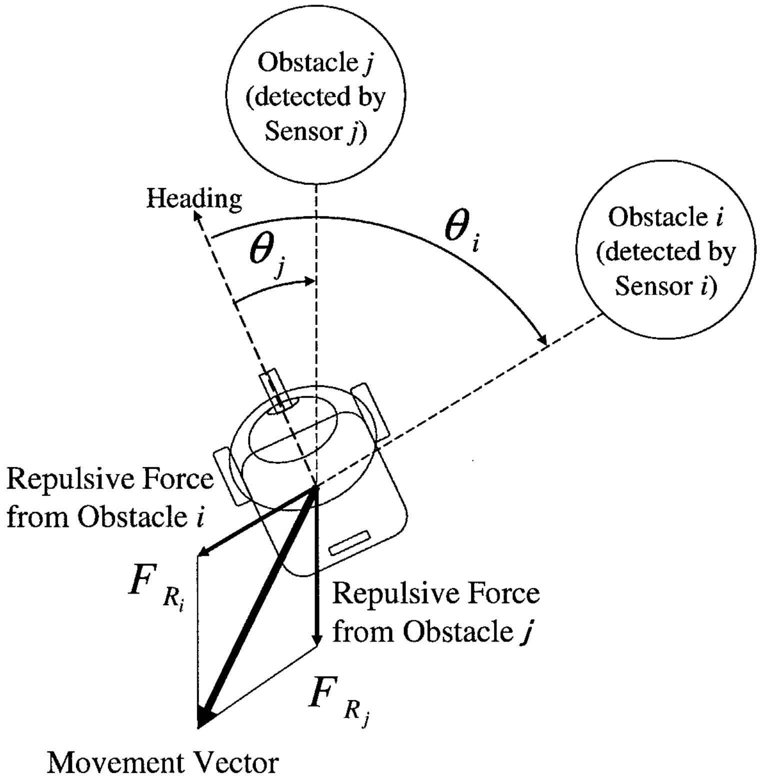


Figure 6.4: Autonomous obstacle-avoidance behavior realized by the potential field method

robot operation responding to and guided by the *changes* in their visual perceptual information.

The parameter ϕ is defined here to quantify a view of a human operator. Figure 6.5 explains its definition. This parameter corresponds to the angle at which the line segment PQ crosses with the horizontal line in the image display window. Table 6.1 summarizes the correlation coefficients between the human steering operation[1] and some ϕ-related values, where averaged values of task execution time represent the individual levels of operational skills. As shown in this table, the correlation coefficient between the steering operation and the value of $\Delta\phi$ (or the temporal difference of ϕ) tends to be positively high, meaning that they are linearly related. For instance, Figure 6.6(a) presents two parallel profiles of the human steering operation and $\Delta\phi$ value, where the shape of its transition is very similar with the $\Delta\phi$'s. This tendency becomes stronger for more skilled operators as the correlation

[1]In this experiment, every human operator little or nothing manipulated the translational velocity during experimental runs, and therefore the robot was almost always under full speed. In addition, the robot autonomy has no ability to drive the robot forward. These are the reasons why the translational velocity was not analyzed.

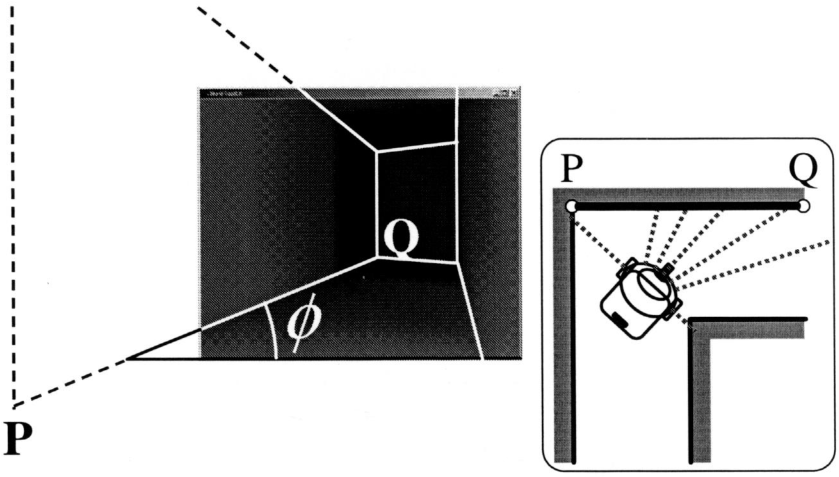


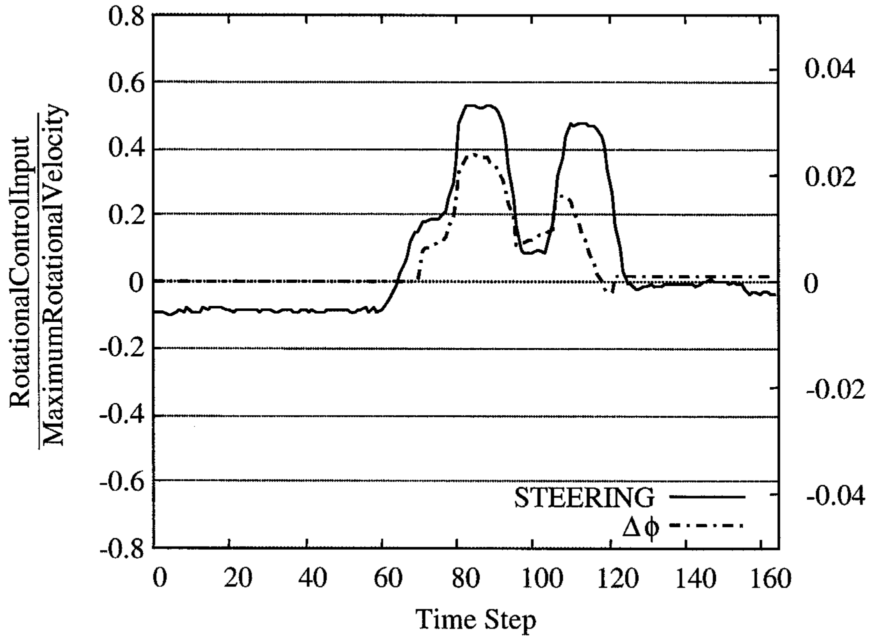
Figure 6.5: Definition of the parameter ϕ to quantify the view of a human operator

Table 6.1: Average correlation coefficients of the human steering operation with the values of ϕ, $\Delta\phi$ (= temporal difference of ϕ), and $\Delta^2\phi$ (= temporal difference of $\Delta\phi$)

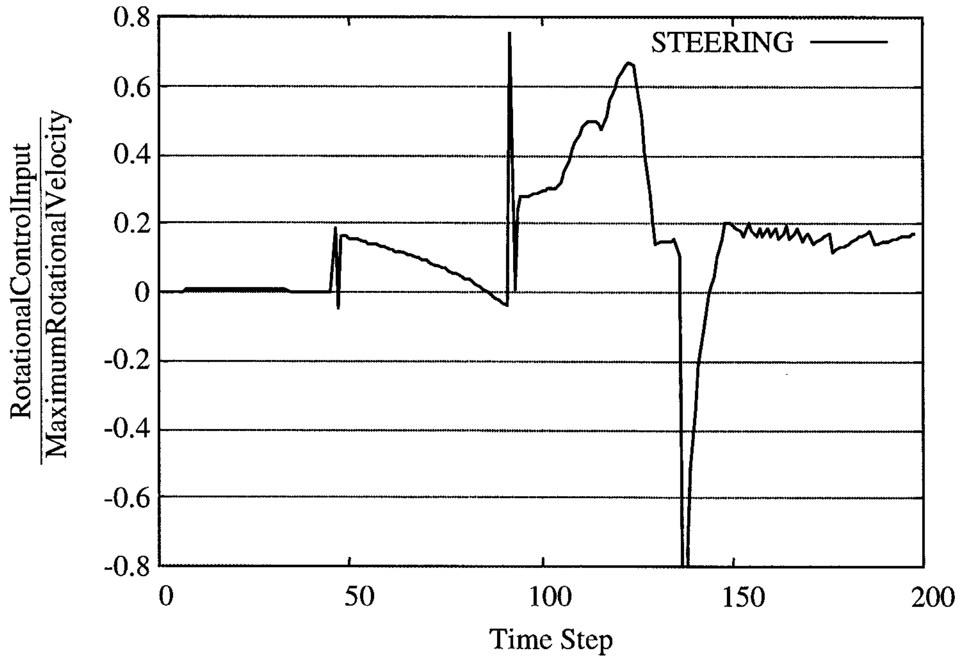
Subject (Avg. run time [sec])	A (5.523)	B (6.093)	C (9.145)	D (9.502)
ϕ	0.364	0.281	−0.098	0.248
$\Delta\phi$	**0.837**	**0.593**	**0.455**	**0.521**
$\Delta^2\phi$	−0.140	−0.190	−0.140	−0.059
Subject (Avg. run time [sec])	E (9.564)	F (9.850)	G (10.094)	H (11.550)
ϕ	0.369	0.188	0.397	0.087
$\Delta\phi$	**0.693**	**0.616**	**0.488**	**0.600**
$\Delta^2\phi$	−0.111	−0.102	−0.071	−0.123

coefficient value between the task execution time and $\Delta\phi$ equals to −0.523 of all the trial data. This result suggests that human (steering) operations would quite depend on the movement structures in their perception like the optical flow rather than momentary data in it (see also the analysis in section 4.4.2). Thus, we can say that the development of the operational skills involves finding out some adequate perceptual cues from such transitional flows, and then realizing proper couplings between those cues and corresponding operations.

In contrast to this feature of human operations, decisions of the machine autonomy depend on very different sensors than the human's. The autonomy controls the robot in response only to a sensory "snapshot" as defined by the equation (6.1), (6.2), and (6.3). Therefore, any radical changes in its sensory perceptions lead to drastic changes in its operations, all of which produce the autonomy's *intermittent*



(a) Human Operation



(b) Mechanical Operation

Figure 6.6: Comparison of steering operations between human (done by the most skillful operator A) and machine autonomies, both of which were recorded from their respective solo performances

or *discontinuous* operations as shown in Figure 6.6(b). This profile illustrates a series of steering operations performed by the machine autonomy only, where all C_i values ($i \in \{1, 2, \ldots, 7\}$) were set to 0.05. Since the robot autonomy has no ability to drive the robot forward, solo performance of the autonomy here was generated by adding the maximum transitional velocity V_{MAX} to the $velocity_{autonomy}$ command during runs. These different cue-utilization styles between the human operators and the machine autonomy do influence their joint activity, especially, human operations.

6.3.3 Effects of Jointed Operation

In the second experiment, the mechanical operations are simply superposed onto the human's, both of which thus equally compose of the robotic behaviors. Three experimental subjects (subject A, D, and E) executed this tele-operation task while all C_i values determining the behavior of the machine autonomy were changed among 0.04, 0.05, 0.06, and 0.07. Where, each operator carried out 3 to 8 experimental trials under the respective C_i conditions (in each condition, all C_is were fixed to the same value). As the result of this experiment, effects of their jointed operation are summarized into the following two aspects:

1. Interventions by the machine autonomy can induce more consistent human operations because they provide good cues on the timing when the human operators need to start steering or turning the robot.

2. Those interventions, however, may harm the operationality of the system from the operators' perspective because the actual system behaviors may deviate from their anticipations due to those interventions.

On the one hand, the mechanized control can afford more precision and consistent judgments in a moment of time than humans can do. Machines can exploit sensory snapshots and rigidly apply those data to some judgmental formulas as associating their perception with certain actions in a one-to-one fashion. Behavioral events triggered by such judgments may sometimes become important cues for the human operators to initiate any actions because the interventions by the machine autonomy can induce human operations to take place at a more consistent timing. As human operators have little perceptual information on the body image of the teleoperator robot, one of the most remarkable evidences for the experienced and skillful human operations involves consistency of the timing when they need to initiate a series of operations for turning at the corner of the corridor. After applying the autonomous obstacle-avoidance behavior to the robot control, enough improvements on this type of operations were confirmed, especially for the immature operators.

On the other hand, any intervening operations by other than his/her own decisions may disorder human operations because they would produce unexpected be-

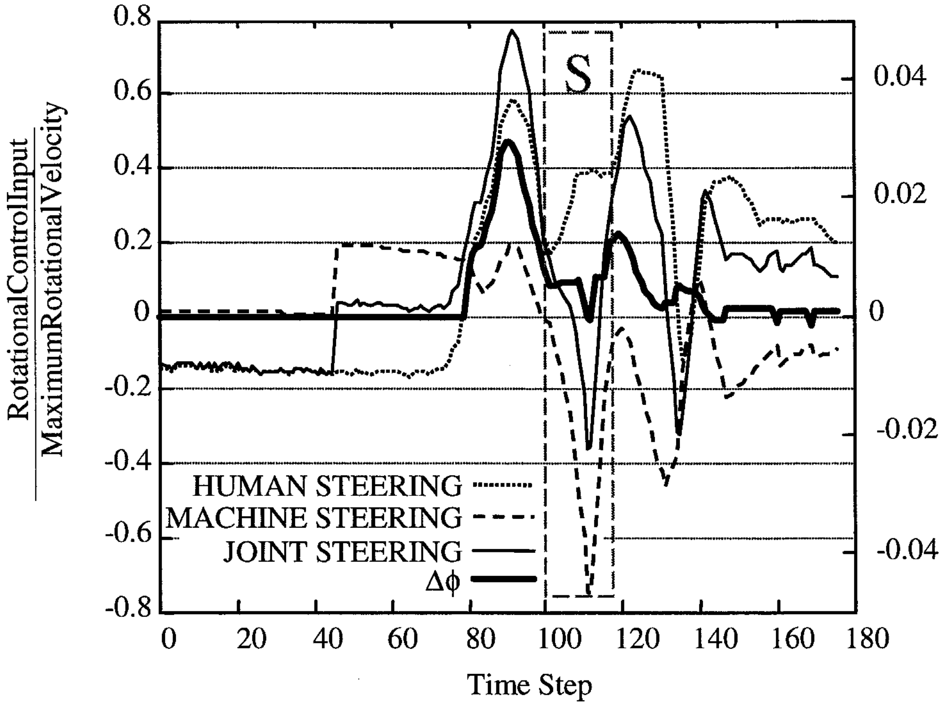


Figure 6.7: Profiles of the individual steering operations and the $\Delta\phi$ value in the human-machine jointed task executions, where the human operator was A and all C_i values were set to 0.05

haviors into the system from his/her perspective. Especially, the larger such unanticipated behavioral deviations, the more drastically reduced the operationality of the system for human operators will become. This kind of matters did be observed in the experimental results here. Figure 6.7 shows instantiating profiles of the individual and jointed steering operations with the data profile of $\Delta\phi$ values in a task execution where human and mechanical operations were simply jointed. Herein, the legends of "HUMAN STEERING", "MACHINE STEERING", and "JOINT STEERING" denote three different profiles of the steering operations, respectively performed by a human operator (subject A), the machine autonomy with $C_i = 0.05$ ($\forall i \in \{1, 2, \ldots, 7\}$), and their combination. In this graph, we can see a series of compensating operations by the human operator in the duration S that is highlighted by a dotted line. At the beginning of this duration, the machine autonomy initiated a fairly strong intervention which caused a large gap of the operator's anticipation form the actual robotic behavior perceived in his vision. As explained in section 6.3.2, human operators are basically guided by the changes in their perceptual information. However, this tightly coupled relation between transitions perceived among visual images and the steering operations in the human control collapsed

Table 6.2: Average correlation coefficients between the steering operations and the value of $\Delta\phi$ in the human-machine simply jointed task executions

C_i	HUMAN	MACHINE	JOINT
0.04	0.667	0.499	**0.868**
0.05	0.550	0.208	**0.769**
0.06	0.604	−0.015	**0.676**
0.07	**0.607**	0.126	0.584

(a) Subject A

C_i	HUMAN	MACHINE	JOINT
0.04	0.408	0.204	**0.833**
0.05	0.523	0.135	**0.725**
0.06	0.644	0.303	**0.760**
0.07	0.677	0.146	**0.844**

(b) Subject D

C_i	HUMAN	MACHINE	JOINT
0.04	0.473	0.298	**0.841**
0.05	0.639	0.348	**0.689**
0.06	**0.727**	0.241	0.638
0.07	**0.695**	0.022	0.573

(c) Subject E

from the autonomy's independent operations there. For such occasions, the human operator was forced to compensate this kind of gaps so that the robotic behaviors actually perceived matched up with his expectations; his operation was adjusted in another sense where their joint steering operations should be coupled with the perceptual changes on the display. Figure 6.7 reveals a shift of the human operation which corresponds to this compensation, that is, very correlated profile of their joint operation with the value of $\Delta\phi$ in the duration S. This prospect is reconfirmed from Table 6.2, which compares the correlation coefficients of $\Delta\phi$ with the steering operations by the human subjects (HUMAN), the machine autonomy (MACHINE), and their integration (JOINT). Where, the experimental subject A, D, and E are the same persons analyzed in Table 6.1. This table proves more intensive correlations between $\Delta\phi$ and JOINT when the machine autonomy has the stronger influences (i.e., lower C_i values) on the system. That is, the stronger interventions by the machine autonomy bring about the more compensatory operations in the human control.

Differences in cognitive function and capability between humans and machines can play an important role to establish their reciprocity for complementing each other in their joint activity. However, mixture of different decision strategies involves potential conflicts among them. Resolution of such unstable relationships in the human-machine collaboration is in principle handed only to human efforts of adaptation. The above experimental results reinforce such view, i.e., coordination by human adaptation in his operational strategy, because the machine autonomy has no ability for their mutual understanding. Hereat, we should consider a framework to deal with the machine adaptation toward more naturalistic human-machine collaboration, where the machine can also coordinate their joint activities with capitalizing the individual functional strengths. One promising approach for this purpose is the co-adaptation to orient the "team" to their common and mutual understandings through their enriched interactions.

6.4 Human-Machine Coordination through Probing Behaviors

6.4.1 Embodiment of Proactive Agency

Based upon the discussions on the proactive agency in section 6.2, a model of mechanical adaptation in the human-machine joint operations is proposed here. The proposed model intends to embody probing behaviors in the machine autonomy, by which the autonomy tries to get more information about the partner's covert decisions for its adaptation purposes. The point is that emergent conflicts between human and mechanical judgments are regarded as the significant opportunities for their coordination. That is, likely occurrences of some problematic human-machine combinations can activate their (here, the mechanical entity side is particularly focused on) probing or exploratory acts directed to the other, and interactions originating from those acts are compared to dialogues toward their mutual understandings. More specifically, residual errors of the autonomy's anticipation from the actual operator's behavior would give possible discrepancies among their operations, and thus they will be applied to the triggering condition for the machine autonomy to commence its new probing behavior. This proactive agency directs the autonomy itself to reduction of uncertainties about the partner's "intention". Iteration and accumulation of those interactions are expected to form some enduring processes toward their flexible or ever-changing collaboration with adequate mutual dependency and reciprocity.

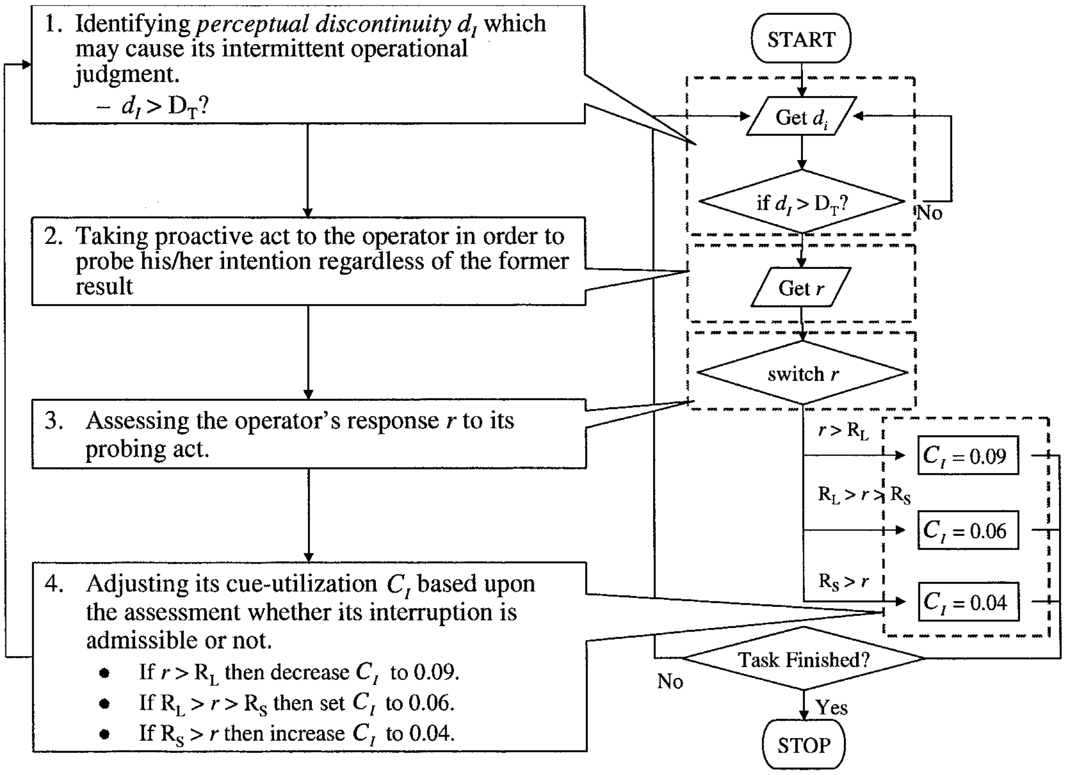


Figure 6.8: Proposed model of mechanical adaptation with probing behaviors

6.4.2 Simple Probing Behavior Specific to Testbed Environment

Under the condition of the simply jointed human-machine operations, complementary operations by the human operators frequently appeared. That was basically caused by intermittent or discontinuous interventions by the machine autonomy which depended on the potential field based on the sensory snapshots. However, as mentioned above, we can also consider such an intervention as a significant opportunity for the operators to expose their intentions in response to the machine autonomy's action. It will become a kind of triggering event after which the machine can acquire other new cues to develop more certain ways to work harmoniously with the human partner.

Based upon this idea, a simple behavioral algorithm of mechanical adaptation was designed and then implemented into the robot autonomy in the simulated shared-control environment here. To be accurate, the machine autonomy must come with some predictive model of the human operations because the autonomy is supposed to exploit discrepancies between its anticipations and the actual partner's behaviors as triggering events for its adaptation. The author, however, put evaluations of their own effects of probing behaviors before developing some human behavioral models now. Therefore, the findings on the human operational skills in section 6.3.2

and 6.3.3 were deployed to the criterion of possible discrepancies between human and mechanical operations: as intermittent or discontinuous interventions by the machine autonomy will induce unnatural complementary operations by human operators, they can be regarded as important events implying possible conflicts between human and machine. Figure 6.8 depictures the employed algorithm, which consists of the following components:

1) Self-aware of Perceptual Discontinuity: In order to detect the perceptual discontinuity, which will cause its intermittent operational judgment, the machine autonomy constantly monitors its sensory snapshots and then their temporal differences.

2) Taking a Proactive Action to Probe the Partner's Intention: When a perceptual discontinuity has been detected, the autonomy *dares to* command its intermittent operation to strongly (or sometimes weakly) intervene the human control at the risk of the operator's confusions.

3) Regard the Partner's Reaction as Expression of Its Intention: After the proactive action, the autonomy assesses the partner's response to it and then decides whether its previous intervention might have been admissible for him/her, or not.

4) Adjusting the Own Way of Intervention: Based upon the assessment, the autonomy revises its way of intervention in favor of their better coordination. This adjustment will be performed so that the autonomy would become humbler if the operator's strong complement (i.e., disagreement) has appeared to the previous intervention while it would become greedier if the operator has made little complements. These two extremes of behavioral adjustment may configure some homeostatic control inside the machine autonomy.

6.4.3 Examining Effects of Proposed Autonomy Behavior

The last experiment was performed using the same shared-control environment as the previous ones, but with the robot autonomy into which the algorithm illustrated in Figure 6.8 was implemented. Figure 6.9 exemplifies varying sensitivities of the respective sensors constantly adjusted by the implemented behavior as performing the joint task.

From this experiment, it was confirmed that the proposed model could successfully reduce complementary operations by the human operators. In order to quantify this result, the amount of fluctuation in the human operations was investigated using the multiple linear regression analysis [9]. As shown in Figure 6.10, the human steering operations are modeled after the Lens Model formalism [6, 15]. They are explained by the distance measurements by the seven range sensors, i.e., SENS1,

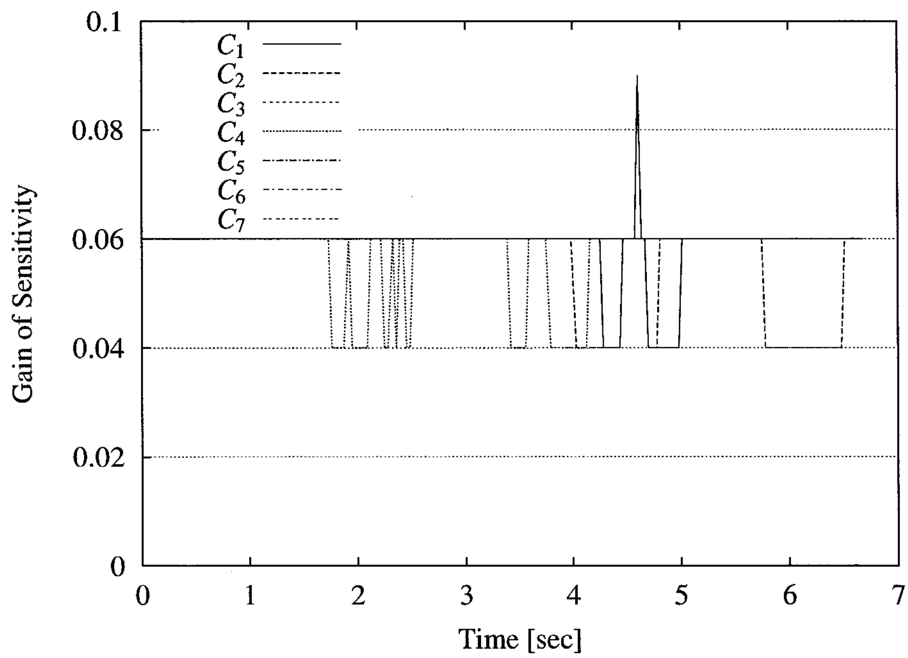


Figure 6.9: Example of varying sensitivities of the respective sensors

SENS2, ..., SENS7 (see Appendix A.1 for details of the general procedure in this method). In the analysis here, a regression model of the human judgments gives a standard, on the basis of which fluctuations of the human steering operation are measured. More specifically, the standard deviation value of modeling errors (i.e., residuals) from the actual human operations is regarded as the amount of fluctuation in his/her operational decision.

As necessary to consider the timing when interventions are made by the machine autonomy, a sequence of each task execution was divided into some segments before applying regression analysis. By segmenting task sequences, situations before and after an autonomy's intervention are expected to be distinguished as different case data. Figure 6.11 summarizes the segmentation procedure. *Hierarchical cluster analysis* using Ward's method is applied to the sensory data in an experimental run, and it produces a dendrogram or a hierarchical, binary cluster tree with rescaled distances among clusters. Based on these outputs, all case data of the sensory measurement vectors are categorized into multiple classes by deciding the threshold value of cluster distance. The clustering point was determined in each profile data so that the number of resultant clusters is equal to four. After segmentalizing profile data, multiple linear regression models of the human steering operation in each case are build using *stepwise model-building technique*, and then the standard deviation values of residual errors of the individual models are examined for the analysis.

As a result of this analysis, Figure 6.12 compares the averaged standard de-

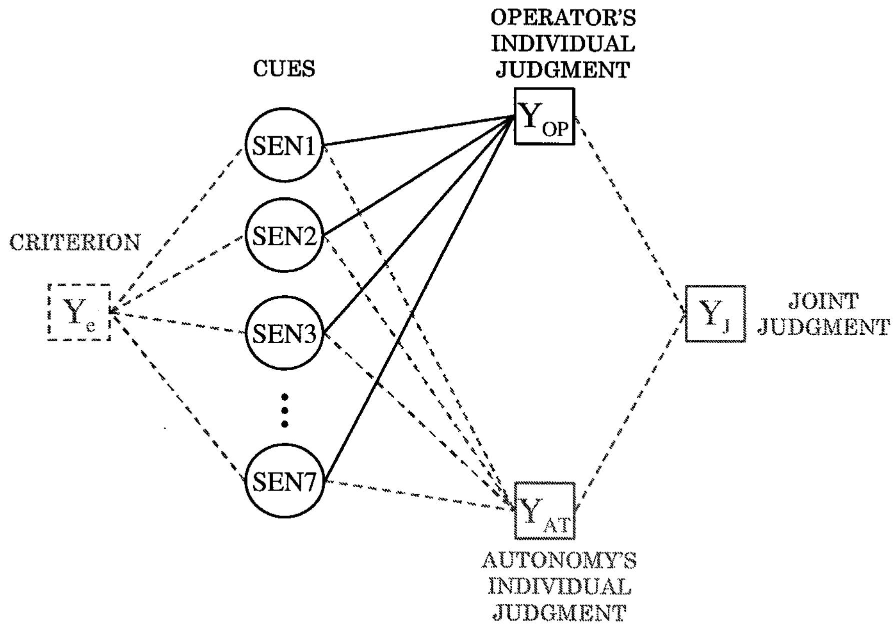


Figure 6.10: Policy capturing of human operations in terms of the Lens Model formalism

viation values of the residuals parallel to the four classes. Where, the legend of "HUMAN SOLO" represents the plot is averaged among solo performances by the human operator while "SIMPLE JOINT" and "PROPOSED MODEL" correspond to the plots of the simply jointed human-machine operations and of the jointed operations with the proposed autonomy, respectively. All the data presented in Figure 6.12 were derived from the performances by the subject A.

From this result, we can see, in all phases but CLASS1, the amounts of "operational fluctuation" are apparently magnified under the SIMPLE JOINT condition from the ones under the HUMAN SOLO condition. Herein, CLASS1 is associated with the phase before any autonomy's interventions. This tendency becomes stronger in the phase of CLASS2 that comes right after strong interventions by the machine autonomy had been done. Those behavioral shifts observable from the two different conditions may at least partly reflect complementary operations by the human operator, which should not have appeared if he could go solo. Those "unnecessary or extra" operations would induce sort of "awkward" interactions between human and machine, as shown in Figure 6.7. On the other hand, attending to the plot of PROPOSED MODEL, those operations were reduced than in the simply jointed human-machine operation. In this way, it is confirmed that the proposed model could successfully mitigate needless complementary operations. Moreover, the proposed autonomy could also capitalize on an advantage of introducing the mechanical operations. In the phase of CLASS1, both SIMPLE JOINT and PRO-

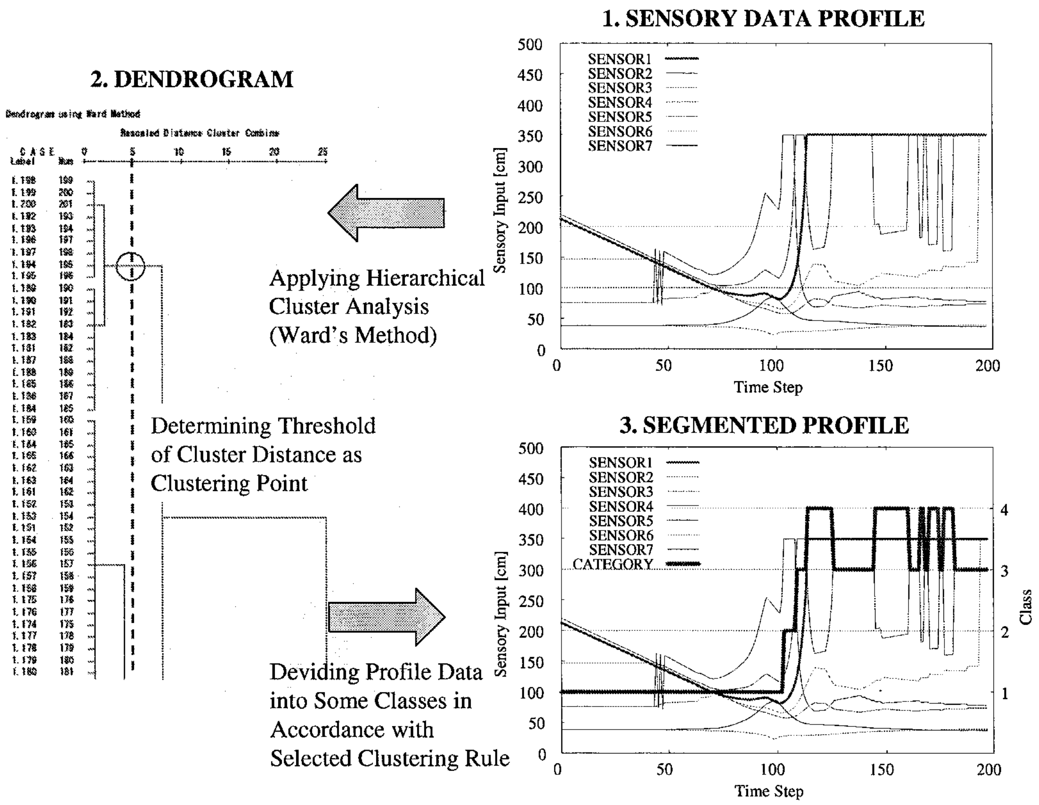


Figure 6.11: Procedure to divide a sequence of task execution into segments

POSED MODEL record smaller fluctuation than the case of HUMAN SOLO. This evidence suggests that human steering operations were performed more consistently in terms of the timing to start turning, by the autonomy's interventions. Therefore, all these results support the perspective that a better form of human-machine coordination could be achieved by implementing the probing behavior for mechanical adaptation.

6.5 Discussions

An appropriate explanation of human cognition is based on the notion of *situatedness* [51]: human cognition is considered to be highly context-dependent or emergent from the interaction between the human and the environment, i.e., the current situation the human is involved in. Those "situated" actions thus render much flexibility in the task ecology. Hence, there exists no absolute scenario to predict actual courses of the interactions such actions set off. Considering this nature of human cognition, those machines to collaborate with humans should have some ability to respond to unexpected events induced by their joint activity and then to

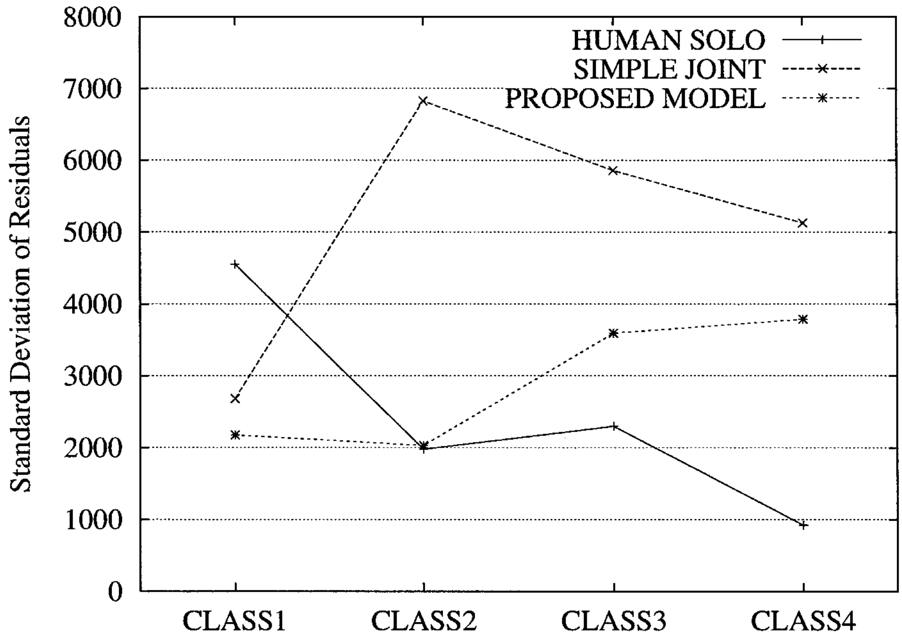


Figure 6.12: Comparison of averaged standard deviation values of residual errors in regression models of human steering operation

develop or repair their adequate relationship on their own initiatives. The concept of co-adaptation the author has introduced aims to represent such requisite aspect of collaborations performed by *both* human- and machine-autonomies towards their synergism, and here has been emphasized especially the role of proving behaviors in their joint activity. Effects of the proposed mechanical adaptation behaviors, or one embodiment of the idea of proactive agency, were examined using a developed shared-control environment. Although its current implementation is confined to a mobile robot navigation task in corridor environments with the autonomy of obstacle-avoidance behavior, it revealed a better coordination could be achieved between a human operator and a machine autonomy.

To be accurate, the machine autonomy must come with some predictive model of the human operations because the autonomy is supposed to exploit discrepancies between its anticipations and the actual partner's behaviors as triggering events for its adaptation. The current experimental configuration, however, has no such model implemented in the machine autonomy. In addition, the investigations that had been performed here is also insufficient in terms of human adaptation because most efforts in this work basically focused on the effects of interventions by the machine autonomy into human operations, in particular, whose strategy has been already established enough. The performances by the unskilled operators under the SIMPLE JOINT (i.e., no mechanical adaptation) condition pointed out both positive and negative effects of mechanical interventions. The former aspect is that they provide human operators with another resource which helps them aware of the consistent timing for turning the robot at the corridor corner. This is a more effective support for unskilled operators. The latter aspect is that those interventions perturb the operators because they introduce into the robot some unexpected behaviors that are hard to be control by the operators without sufficient coping skills. The more intensive interventions the autonomy performs, the stronger this tendency becomes, eventually into worse collaborative performances. In order to investigate the differences among operators with different skill level and the adaptation process in a particular operator, some quantification method to capture the human decision structure is necessary. For this approach, the Lens Model framework [4, 6, 15] seems to have potentials as examined in the study [39].

6.6 Summary

This chapter addressed necessary elements for the adequate coordination between the human operation and the mechanized control, especially focusing on the adaptability in the human-machine collaboration. At first, using a simulated shared-control environment of a mobile robot by a human operator and a machine autonomy, the effects of the human-machine joint activity were analyzed in terms of the possible disorder between the human operator and the machine autonomy due to their different cognitive natures.

Then next, inspired by the humans' proactive actions to their external world, i.e., *epistemic actions*, it has been proposed to introduce probing behaviors into the machine autonomy for its adaptation. Those behaviors are actuated to reduce the uncertainty about its understanding of the partner's "intention", in accordance with the discrepancy between the anticipated and the actual decision of the human operator; if the gap between them becomes large, the machine autonomy ventures to perform the actions that may introduce confusion to the partner, and then see how he/she reacts. The operator's reactions will be exploited for the adjustment of the autonomy's decision structure. This proposed behavior was implemented as simple algorithm for the machine adaptation in the testbed shared-control environment. The experimental results revealed that the good coordination of the human operation and the automated behavior could be achieved.

Finally, the discussions were made about the feasibility of this approach towards the well-coordinated human-machine relationship. Although the conflicts caused by the differences between the human and machine autonomy's judgment strategies may disorder their collaboration, they can also be regarded as the significant opportunities for their adaptation. We should note that perpetual iteration and accumulation of such experiences form the dynamism of their "co"-adaptation in human-machine systems.

Chapter 7

Concluding Remarks

Toward the making of "human and technology ensembles", their communication is one of the most critical elements to bridge gaps between them. Human-machine interaction design is to give automated systems a kind of *sociality* to their human partners. Concerning this issue, this dissertation enclosed the research works performed from a new perspective of "co-adaptive interface" for human-machine systems. Hereafter, the summaries of the respective chapters are described.

Chapter 2 explained the basic approach of this dissertation to the human-machine interaction design issues, and then introduced a new concept of co-adaptive interface that facilitates mutual adaptation processes between humans and machines.

Chapter 3 examined the feasibility of the facilitating systems which can mediate the interaction between the human operator and the teleoperator robot, by introducing a new concept of *intertask morphology*. This idea for human-machine interface design aims at connecting two different behavioral tasks via their structural isomorphism, and then extending the operator's actual perception-action cycles to the ideal perception-action cycles with his/her distal attribution established. From the perspective of intertask morphology, careful analyses have been done to find out the invariant structures that are common between two behavioral tasks in a VR-based (i.e., virtual reality based) tele-operation; the one task was configured in the VR space, in which a human subject hits a coming ball into the target area with his hand, while the other was done in the real world where a teleoperator mobile robot catches a coming ball with its body like a goalkeeper. Both of these tasks were analyzed into four qualitatively different phases, suggesting the possibility of the behavioral mapping between them. The common form of the decomposition of these behavioral task structures was computerized by the Grossberg's ART (i.e., Adaptive Resonance Theory) neural network model, which can detect the boundaries of those phases during the human operator's performing tasks in real time. This computerization was exploited so as to cancel the effects of the time-delay and discontinuity in the VR-based tele-operation, by deforming objects in the VR space corresponding to the abstract behavioral phases derived from the ART model.

Chapter 4 investigated human skills to operate a mobile robot in a tele-operation environment, where the human operators confront with the considerable difficulties in developing their accurate situation awareness of the site explored remotely and making the appropriate responses to those situations. In order to make full use of the teleoperator robot for the search tasks, the operators must develop the skills to read off the meanings of the proximal information as the actual events in the distance, in addition to the ones to operate the robot. The experimental results revealed that the accurate and effective operations require the adequate view control of the camera which enables the parallel execution of the two different activities for the robotic ambulatory movement and for the accurate situation awareness. This operational strategy was analyzed from the two perspectives. The one analysis was done based upon the optical-flow analysis of view image from the onboard camera during a series of ambulatory movements around covered objects. The other analysis was performed by decomposing a series of operations into the transitions of some subordinate activities. Both of the analyses explain that what's necessary to be *externalized* is the information for accurately orienting the remote robot in its task environment.

Chapter 5 provided a formal approach to designing effective human-machine interaction channels between a human operator and a machine autonomy in their shared-control situations. After the qualitative classification of information types defined in Kirlik's *Generalized Lens Model* framework, variables in that human-machine system were distinguished in terms of "proximal or distal" from both perspectives of perception and action for each decision-maker, as well as their latent covariant relations were depictured. Based upon the fundamental philosophy that any collaborative human-machine systems need to accommodate human and machine-autonomy's variable actions including their *epistemic actions*, a new human-robot collaboration style has been proposed with the *shared communicational modality* between them. The proposed interaction model embodies their communicational modality by imposing the mutual constraints between their respective [PP,PA] (i.e., proximal for both perception and action) variables. This embedded connection between the two decision-makers can increase each agent's opportunity to adjust their operational strategies to the other's behavior, and thus promotes their mixed-initiative interactions. According to this guiding principle, an experimental shared-control environment composed of a human operator and an autonomous mobile robot was developed, in which a joystick with the force-feedback effect generator is utilized to embody the shared communicational modality. By letting the intentions of the robot autonomy transfer onto the joystick using the feedback force, the autonomy can also manipulate the joystick as well as the operator. Thus, the operator's and the autonomy's input actions are mutually restricted through that joystick, since both of them can manipulate it and affect the other's judgment policies. This actual experimental environment was used to verify the shared communicational modality providing with the direct access to the significant property of their joint judgment for adequate revisions of their individual judgment policies and their adequate role-assignments.

Chapter 6 addressed necessary elements for the adequate coordination between the human operation and the mechanized control, especially focusing on the adaptability in the human-machine collaboration. A simulated shared-control environment composed of a human operator and a machine-autonomy was utilized to analyze the effects of the human-machine joint activity in terms of the possible disorder between the human operator and the machine-autonomy due to their different cognitive natures. Inspired by the humans' proactive actions to their external world, i.e., *epistemic actions*, it has been proposed to introduce probing behaviors into the machine-autonomy for its adaptation. Those behaviors are actuated to reduce the uncertainty about its understanding of the partner's "intention", in accordance with the discrepancy between the anticipated and the actual decision of the human operator; if the gap between them becomes large, the machine-autonomy ventures to perform the actions that may introduce confusion to the partner, and then see how he/she reacts. The operator's reactions will be exploited for the adjustment of the autonomy's decision structure. This proposed behavior was implemented as simple algorithm for the machine adaptation in the testbed shared-control environment. The experimental results revealed that the good coordination of the human operation and the automated behavior could be achieved. The point is that the conflicts caused by the differences between the human and machine-autonomy's judgment strategies can also be regarded as the significant opportunities for their adaptation although they may disorder their collaboration, and that perpetual iteration and accumulation of such experiences form the dynamism of their *co*-adaptation in human-machine systems.

It is infeasible to design "the height of human-machine collaboration" by any *external* designers in advance. Rather, some self-regulating mechanism is necessary so that human-machine systems themselves can constantly coordinate their internal communicative structures as considering the dynamics emerged from actual interactions among their subsystems. From this perspective, machine autonomies should be open to modification or revision for the sake of facilitation of the human-environment interactions they mediate. Their own behavioral adaptation will be performed not only to their task environments but also to their human *partners*. The author believes, the machines capable of conducting socially epistemic actions would adequately discriminate information utilized for adaptation purposes, and then embodiments of shared communicational modality would effectively mediate bilateral information flows between human and mechanical entities toward their flexible or ever-changing collaborations.

Appendix A

Analytical Methods for Human-Machine Interaction

A.1 Lens Model

Brunswik's Lens Model is a functional description of judgment behavior, particularly as instantiated in the area of Social Judgment Theory [4, 6, 15, 48]. Along with "policy capturing", which traditionally refers to multiple regression modeling of judgments made on a series of profiles, the Lens Model provides a systematic approach to human judgment in the task environment. This analysis methodology has been successfully utilized to examine a diverse set of issues including clinical judgment, conflict resolution, interpersonal learning, expertise, and the types of feedback that promote learning.

The most essential property of the Lens Model is on providing dual symmetric models of both the human judge and the environment, by which the two are described in an integrated fashion [25]. Figure A.1 depicts an overview of this model. The task environment, i.e., (*ecology*), is represented in the left half of the figure, where the human judge or (*subject*) is represented on the right half.

On the one hand, the ecology is described as consisting of three different kinds of elements, in terms of the *proximal versus distal* distinction in human perception, as follows:

a) **Cues** (X_i's) represents *proximal* information whose states are directly measurable to the subject;

b) **Ecological criterion** (Y_e) corresponds to *distal* event in that the subject cannot perceive its actual state and that it has to be judged; and

c) **Ecological validity** ($r_{e,i}$) renders the causal relationship between the cues and the criterion, which may vary and take various forms.

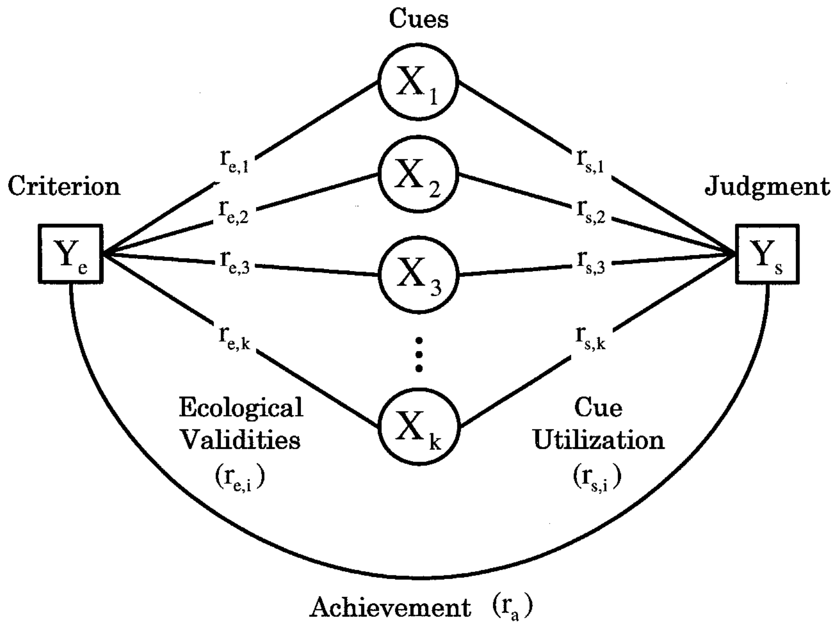


Figure A.1: Brunswiki's Lens Model adapted for the study of human judgment

Where, the "proximal" refers the direct accessibility by the subject while the "distal" represents the indirectness as being accessed via corresponding proximal information. That is, the distal criterion must be inferred by the judge on the basis of the proximal cues available.

On the other hand, the left side of the figure describes the human **judgment** (Y_s) about the distal event. The subject has a set of the cues available to judge an ecological criterion. The ways in the subject makes use of the cues to arrive at a judgment is called as **cue utilization** ($r_{s,i}$), and may take various forms.

Linear regression is the most prevalent method of inferring possible judgment strategies from behavioral data. Applied to a series of judgment profiles, regression analysis yields a linear-additive model of the judgment which represents how the subject might weight and combine the probabilistic cues in order to render her judgment or prediction about the state of the world. In usual applications of the Lens Model analysis, judgments are captured as the subject's judgment policy by such a linear combination of the cues, as well as an ecological criterion. That is, the ecological validity or utilization of a cue can be expressed as a correlation between the cue value and the criterion or judgment, respectively.

As mentioned above, the Lens Model represents the judgment-environment system as a symmetrical structure, in which the dual models are based on the same environmental information, i.e. the cues. This symmetry allows the modeler to formally measure the degree of fit between the human judge and the demands of the judgment task. For instance, we can assess judgment success, or achievement, by

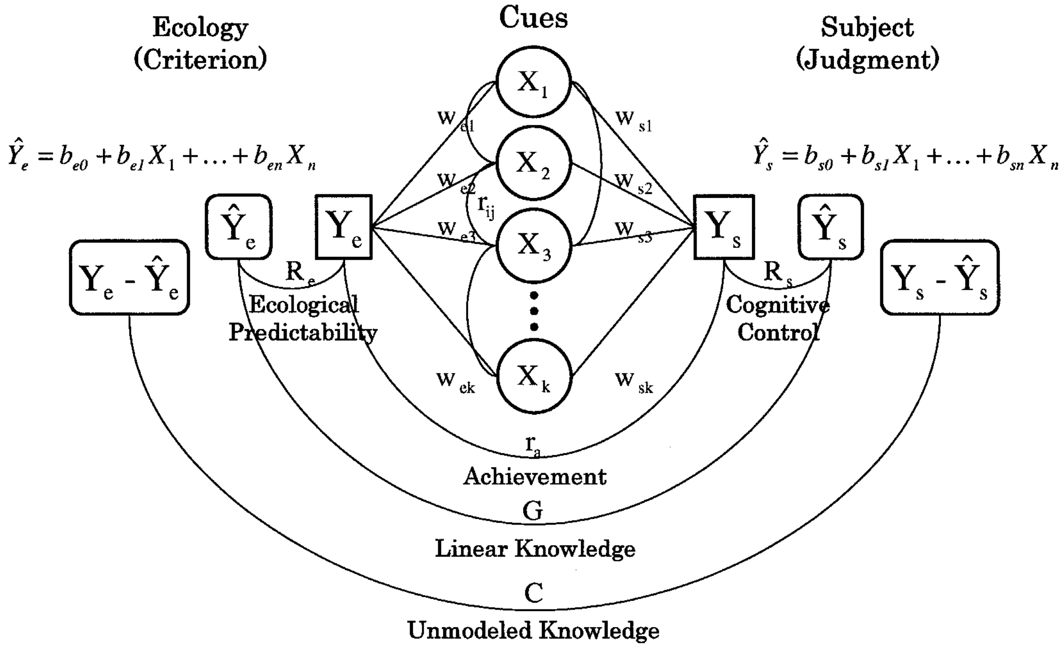


Figure A.2: The Lens Model with superimposed statistical parameters for comparing judgment and task ecology (from [6])

examining the correspondence between the actual criterion value and the judgment. At the same time, the extent to which the subject makes judgments consistently can also be measured with relation to a linear judgment policy model, as well as the predictability of the environment. The Lens Model formalism has some parallel indices, called *Lens Model Equation (LME) Parameters*, that are utilized for these investigations on the two interacting systems [6].

Figure A.2 illustrates the parameters superimposed on the Lens Model diagram. In that, the multiple linear regression model of the judge is formulated as

$$Y_s = \hat{Y}_s + e \tag{A.1}$$

where

$$\hat{Y}_s = w_{s1}X_1 + w_{s2}X_2 + \ldots + w_{sk}X_k, \tag{A.2}$$

w_{sk} are weights and e is the residual. A corresponding multiple regression model is given for the ecology as

$$Y_e = \hat{Y}_e + e \tag{A.3}$$

where

$$\hat{Y}_e = w_{e1}X_1 + w_{e2}X_2 + \ldots + w_{ek}X_k. \tag{A.4}$$

In these two models, the actual and judged criterion values are modeled as linear combinations of the cue values, which link the criterion values and coded cue values. When given this formalization, all the Lens Model parameters are defined as follows.

Cognitive control: $\mathbf{R_s}$ gives the correlation between Y_s and $\hat{Y}_s$, shown in Figure A.2 as linking actual to predicted judgments. This parameter represents the *cognitive control* of the judge, and measures how well the judgments could be predicted with a linear combination of the cue values. A higher indicates that the subject is making judgments more consistently with respect to a single judgment model.

Ecological predictability: For the environmental model, $\mathbf{R_e}$ represents the predictability of the criterion, shown in Figure A.2 as linking actual to estimated criterion values. This parameter represents the *ecological predictability*, and measures how well the value of the ecological criterion could be predicted with a linear combination of the cue values. That is, it measures the adequacy of a linear model of the environment.

Linear knowledge: The correlation between $\hat{Y}_s$ and $\hat{Y}_e$ is labeled as $\mathbf{G}$ and called *linear knowledge*, shown in Figure A.2 as a link between predicted judgments and predicted criterion values. This parameter denotes the linear correspondence between the subject's judgment policy and the optimal model of the criterion, and measures how well the predictions of the model of the human judge match predictions of the model of the environment. Thus, it reflects how well a modeled judgment policy captures the linear structure in the environment.

Unmodeled knowledge: As against the *linear knowledge*, the correlation between the two sets of the residuals, i.e., $Y_s - \hat{Y}_s$ and $Y_e - \hat{Y}_e$, is commonly called *unmodeled knowledge* and labeled as $\mathbf{C}$. This parameter, shown in Figure A.2 as a line linking the differences between predicted and actual criterion values, measures the extent to which the subject's policy collectly employed unmodeled cues in judging the criterion is obtained. It suggests that if the residual variance is systematic, the judge is using a nonlinear policy effectively. A high value for $\mathbf{C}$ represents a judge's reasonably accurate application of her knowledge of predictive but unmodeled relationships in the ecology.

Achievement: The remaining term, $\mathbf{r_a}$, is the *achievement* of the judge as measured by the linear correlation between judgments and the criterion, shown in Figure A.2 as a line linking judgments to criterion values. This parameter represents the correlation between the actual ecological criterion values and the subject's actual judgment ratings, and can be interpreted as the extent to which judgments and criterion values agree. A high value for $\mathbf{r_a}$ would represents the situation where criterion values and judgment ratings closely agree.

Therefore it evaluates subject performance in the sense of correspondence or accuracy.

The entire set of these statistics are related by the Lens Model, and bear a specific analytical relationship to each other. This analytical relationship is embodied in a decomposition representation known as the Lens Model Equation (LME). The LME is

$$r_a = GR_eR_s + C\sqrt{(1 - R_e^2)}\sqrt{(1 - R_s^2)}. \tag{A.5}$$

The equation formulates a judge's performance (or achievement) in a task in terms of the two components that account for *linear* (GR_eR_s) and *nonlinear* correlations ($C\sqrt{(1 - R_e^2)}\sqrt{(1 - R_s^2)}$). The first component corresponds to the one of the achievement correlation which can be attributed to the explicit linear modeling of ecology and judgment process. The second component, traditionally termed the configural component, represents the contribution to overall achievement by the *unmodeled* aspects of the ecology and of judgments. The LME indicates that these components can be considered separately in examining judgment performance.

In this way, the Lens Model can represent how both environmental and cognitive structure mutually contribute to judgment performance, and can give us an approach useful for identifying characteristics of successful performance on a judgment task.

A.2 Generalized Lens Model

The original Lens Model makes the *proximal versus distal* distinction of the environmental structure *only* about human perception, wherein the "proximal" refers the direct perceptibility from the human judge while the "distal" represents the indirectness as being accessed via the corresponding proximal information. This model is, however, insufficient to deal with the proactive human-machine interactions various forms of epistemic actions involve, as Kirlik remarked as below in [26].

> "A major deficiency of the Lens model is that it portrays of view of the organism without any control over the environmental structure to which it must adapt. This is because there are no resources within this model to describe how an organism might use action to adapt the environment to its own needs and capabilities."

Therefore, "adding such resources requires elaborating the Lens model with resources describing the proximal/distal structure of action, in addition to the proximal/distal structure of perception" [25, 26]. He has proposed *Generalized Lens Model* as adding the "proximal/distal structure of action" into the original Lens Model scheme. Analogous to the perspective of perception, variables in the task environment are considered to be proximal or distal from the perspective of action.

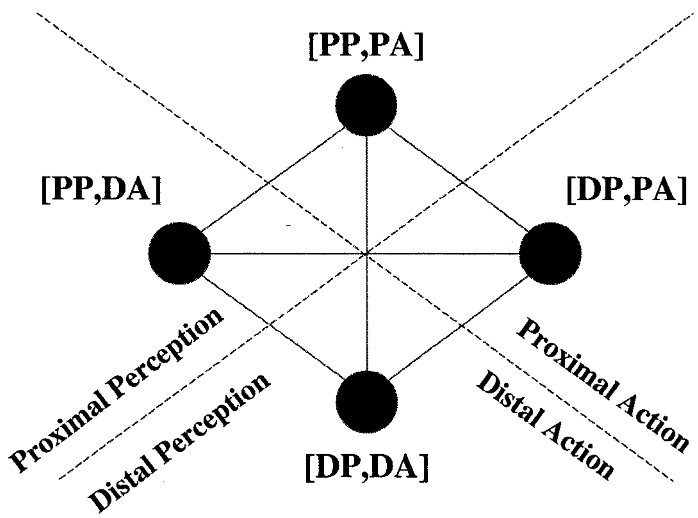


Figure A.3: Kirlik's Generalized Lens Model (from [26])

That is, those variables are to be proximal from the perspective of action whose values can be directly or immediately manipulated by the performer. By contrast, the variables are to be distal from the perspective of action if their values cannot be so changed and instead can be changed only by manipulating other proximal variables over which the performer has direct control. Figure A.3 illustrates Kirlik's Generalized Lens Model.

With the resources to describe the action status, the model has four types of variables in the task environment with potential constraint relationships among them. As shown in Figure A.3, environmental variables can be classified into four different types of information as follows:

I **[PP,PA]**: a variable that is proximal for both perception and action (i.e., Proximal Perception and Proximal Action);

II **[PP,DA]**: a variable that is proximal for perception but distal for action (i.e., Proximal Perception and Distal Action);

III **[DP,PA]**: a variable that is distal for perception but proximal for action (i.e., Distal Perception and Proximal Action); and

IV **[DP,DA]**: a variable that is distal for both perception and action (i.e., Distal Perception and Distal Action).

Bibliography

[1] Allen, J. F. Mixed-Initiative Interaction. *IEEE Intelligent Systems*, Vol. 14, No. 5, pp. 14–16, 1999.

[2] Barber, K. S. and C. E. Martin. Agent Autonomy: Specification, Measurement, and Dynamic Adjustment. Proceedings of the Autonomy Control Software Workshop at Autonomous Agents 1999 (Agents'99), pp. 8–15, Seattle, May 1999.

[3] Billings, C. E. *Aviation Automation: The Search for a Human-Centered Approach.* Lawrence Erlbaum Associates Inc., Mahwah, NJ, 1996.

[4] Brunswik, E. Representative Design and Probabilistic Theory in a Functional Psychology. *Psychological Review*, Vol. 62, pp. 193–217, 1955.

[5] Carpenter, G., S. Grossberg, and D. Rosen. Fuzzy ART: Fast Stable Learning and Categorization of Analog Patterns by an Adaptive Resonance System. *Neural Networks*, Vol. 4, pp. 759–771, 1991.

[6] Cooksey, R. W. *Judgment Analysis: Theory Methods and Applications.* Academic Press, 1996.

[7] Degani, A. *Taming HAL: Designing Interfaces Beyond 2001.* Palgrave Macmillan, 2004.

[8] Dorais, G., R. P. Bonasso, D. Kortenkamp, B. Pell, and D. Schreckenghost. Adjustable Autonomy for Human-Centered Autonomous Systems on Mars. Proceedings of the First International Conference of the Mars Society, August 1998.

[9] Draper, N. R. and H. Smith. *Applied Regression Analysis.* John Wiley & Sons, Inc., 1966.

[10] Fel'dbaum, A. A. *Optimal Control Systems.* Academic Press, New York, NY, 1965.

[11] Ferguson, G. and J. F. Allen. TRIPS: An Integrated Intelligent Problem-Solving Assistant. Proceedings of the Fifteenth National Conference on AI, 1998.

[12] Ferguson, G., J. F. Allen, and B. Miller. TRAINS-95: Towards a Mixed-Initiative Planning Assistant. Proceedings of Third Conference on Artificial Intelligence Planning Systems, pp. 70–77, Edinburgh, Scotland, 1996.

[13] Gibson, J. *The Ecological Approach to Visual Perception.* Houghton Mifflin, Boston, MA, 1979.

[14] Grossberg, S. Competitive Learning: From Interactive Activation to Adaptive Resonance. *Cognitive Science*, Vol. 11, pp. 23–63, 1987.

[15] Hammond, K. R. *Human Judgment and Social Policy: Irreducible Uncertainty, Inevitable Error, Unavoidable Injustice.* Oxford University Press, March 1996.

[16] Hancock, P. A. and M. H. Chignell. On Human Factors. Global Perspectives on the Ecology of Human-Machine Systems (eds.Flach, J., P. A. Hancock, J. Caird, and K. J. Vicente), Vol. 1 of *Resources for Ecological Psychology*, chapter 2, pp. 14–53. Lawrence Erlbaum Associates Inc., 1995.

[17] Heins, L. and D. Tauritz. Adaptive Resonance Theory (ART): An Introduction. Technical Report IR-95-35, Department of Computer Science, Leiden University, 1995.

[18] Hirai, S. Theory of Shared Autonomy. *Journal of the Robotics Research in Japan*, Vol. 11, No. 6, pp. 20–25, 1993. (in Japanese).

[19] Holland, J. H., K. J. Holyoak, R. E. Nisbett, and P. R. Thagard eds. *Induction: Processes of Inference, Learning, and Discovery.* The MIT Press, 1986.

[20] Horvitz, E. Uncertainty, Action, and Interaction: In Pursuit of Mixed-Initiative Computing. *IEEE Intelligent Systems*, Vol. 14, No. 5, pp. 17–20, 1999.

[21] Hutchins, E. *Cognition in The Wild.* The MIT Press, Cambridge, MA, 1995.

[22] Hutchins, E. How a Cockpit Remembers Its Speeds. *Cognitive Science*, Vol. 19, pp. 265–288, 1995.

[23] Jingu, H. *Skill No Ninchi Kagaku: Koudou No Program Wo Kangaeru.* KAWASHIMA SHOTEN, 1993. (in Japanese).

[24] Kawato, M., et al. *Undou.* Iwanami Kouza: Ninchi Kagaku 4. Iwanami Shoten, Publishers, 1994. (in Japanese).

[25] Kirlik, A. Requirements for Psychological Models to Support Design: Toward Ecological Task Analysis. Global Perspectives on the Ecology of Human-Machine Systems (eds.Flach, J., P. A. Hancock, J. Caird, and K. J. Vicente), Vol. 1 of *Resources for Ecological Psychology*, chapter 4, pp. 68–120. Lawrence Erlbaum Associates Inc., 1995.

[26] Kirlik, A. The Ecological Expert: Acting to Create Information to Guide Action. Proceedings of Fourth Symposium on Human Interaction with Complex Systems, pp. 15–27, 1998.

[27] Kirlik, A., R. Miller, and R. Jagacinski. Supervisory Control in a Dynamic and Uncertain Environment: A Process Model of Skilled Human-Environment Interaction. *IEEE Transactions on System, Man, and Cybernetics*, Vol. 23, No. 4, pp. 929–951, 1993.

[28] Kirsh, D. The Intelligent Use of Space. *Artificial Intelligence*, Vol. 73, pp. 31–68, 1995.

[29] Kirsh, D. and P. P. Maglio. On Distinguishing Epistemic from Pragmatic Action. *Cognitive Science*, Vol. 18, pp. 513–549, 1994.

[30] Loomis, J. M. Distal Attribution and Presence. *Teleoperation and Virtual Environments*, Vol. 1, No. 1, pp. 113–119, 1992.

[31] Neisser, U. *Cognition and Reality: Principles and Implications of Cognitive Psychology*. W. H. Freeman and Company, 1976.

[32] Parasuraman, R., T. B. Sheridan, and C. D. Wickens. A Model for Types and Levels of Human Interaction with Automation. *IEEE Transactions on Systems, Man, and Cybernetics, Part A*, Vol. 30, No. 3, pp. 286–297, 2000.

[33] Pfeifer, R. and C. Scheier. *Understanding Intelligence*. The MIT Press, Cambridge, Massachusetts, 1999.

[34] Polanyi, M. *The Tacit Dimension*. Routeledge and Kegan Paul, London, 1966.

[35] Raskin, J. *The Humane Interface: New Directions for Designing Interactive Systems*. Addison-Wesley Professional, March 29 2000.

[36] Rasmussen, J. *Information Processing and Human-Machine Interaction: An Approach To Cognitive Engineering*. North-Holland, 1986.

[37] Salas, E., J. A. Cannon-Bowers, S. M. Fiore, and R. J. Stout. Cue-Recognition Training to Enhance Team Situation Awareness. New Trends in Cooperative Activities: Understanding System Dynamics in Complex Environments, pp. 169–190. Human Factors & Ergonomics Society, Santa Monica, CA, 2001.

[38] Sarter, N. B., D. D. Woods, and C. E. Billings. Automation Surprises. Handbook of Human Factors & Ergonomics (ed.Salvendy, G.). Wiley, 2nd edition, 1997.

[39] Sawaragi, T., Y. Horiguchi, and M. Ishizuka. Modeling ecological expert: comparative analysis of human skill development with fuzzy controller. *Soft Computing*, Vol. 7, No. 3, pp. 140–147, 2003.

[40] Sayeki, Y. Interface No Ninchi Kagaku. Mathematical Sciences, No. 297, pp. 5–9. SAIENSU-SHA Co., Ltd., 1988. (in Japanese).

[41] Sayeki, Y. Kikai To Ningen No Jouhou Shori: Ninchi Kougaku Josetsu. Imi To Jouhou (ed.Takeuchi, K.), pp. 21–54. University of Tokyo Press, 1988. (in Japanese).

[42] Sayeki, Y. and M. Sasaki eds. *Active Mind: Ningen Ha Ugoki No Naka De Kangaeru.* University of Tokyo Press, 1990. (in Japanese).

[43] Scallen, S. F. and P. A. Hancock. Implementing Adaptive Function Allocation. *International Journal of Aviation Psychology*, Vol. 11, No. 2, pp. 197–221, 2001.

[44] Scallen, S., P. Hancock, and J. Duley. Pilot Performance and Preference for Short Cycles of Automation in Adaptive Function Allocation. *Applied Ergonomics*, Vol. 26, No. 6, pp. 397–403, December 1995.

[45] Scerri, P., D. V. Pynadath, and M. Tambe. Towards Adjustable Autonomy for the Real World. *Journal of Artificial Intelligence Research*, Vol. 17, pp. 171–228, 2002.

[46] Shapiro, D. and R. Schmidt. The Schema Theory: Recent Evidence and Developmental Implications. The Development of Movement Control and Coordination (eds.Kelso, J. and J. Clark), pp. 113–150. John Wiley & Sons, 1982.

[47] Sheridan, T. B. *Telerobotics, Automation, and Human Supervisory Control.* The MIT Press, 1992.

[48] Sheridan, T. B. *Humans and Automation: System Design and Research Issues.* Wiley Series in Systems Engineering and Management. Wiley-Interscience, July 2002.

[49] Shneiderman, B. *Designing the User Interface: Strategies for Effective Human-Computer Interaction.* Addison Wesley Longman, Inc., third edition edition, 1998.

[50] Sierhuis, M., et al. Human-Agent Teamwork and Adjustable Autonomy in Practice. Proceeding of the 7th International Symposium on Artificial Intelligence, Robotics and Automation in Space, Nara, Japan, May 2003.

[51] Suchman, L. A. *Plans and Situated Actions: The Problem of Human-Machine Communication.* Cambridge University Press, 1987.

[52] Vicente, K. J. A Few Implications of an Ecological Approach to Human Factors. Global Perspectives on the Ecology of Human-Machine Systems (eds.Flach, J., P. A. Hancock, J. Caird, and K. J. Vicente), Vol. 1 of *Resources for Ecological Psychology*, chapter 3, pp. 54–67. Lawrence Erlbaum Associates Inc., 1995.

[53] Vicente, K. J. *The Human Factor: Revolutionizing the Way People Live With Technology.* Routledge, March 2004.

[54] Vicente, K. J. and J. Rasmussen. The Ecology of Human-Machine Systems II: Mediating "Direct Perception" in Complex Work Domain. *Ecological Psychology*, Vol. 2, No. 3, pp. 207–249, 1990.

[55] Vicente, K. J. and J. Rasmussen. Ecological Interface Design: Theoretical Foundations. *IEEE Transactions on Systems, Man and Cybernetics*, Vol. 22, No. 4, pp. 589–606, 1992.

[56] Wickens, C. D., A. S. Mavor, and J. P. McGee eds. *Flight to The Future: Human Factors in Air Traffic Control.* National Academy Press, Washington, D.C., 1997.

[57] Woods, D. D. and E. S. Patterson. How Unexpected Events Produce an Escalation of Cognitive and Coordinative Demantds. Stress, Workload and Fatigue (eds.Hancock, P. A. and P. A. Desmond), pp. 290–304. Lawrence Erlbaum Associates Inc., Hillsdale, NJ, 2001.

[58] Wright, P., B. Fields, and M. Harrison. Analysing Human-Computer Interaction as Distributed Cognition: The Resources Model. *Human Computer Interaction*, Vol. 15, No. 1, pp. 1–42, 2000.

[59] Zhang, J. External Representations in Complex Information Processing Tasks. Encyclopedia of Microcomputers (eds.Kent, A. and J. G. Willisms). Marcel Dekker Inc., New York, 2001.

Published Papers

Journal Papers

1. Tetsuo Sawaragi and Yukio Horiguchi, "Analysis of Task Morphologies for Networking Behavioral Skill via Virtual Reality", *ACM Journal of Intelligence: New Visions of AI in Practice*, Vol. 11, No. 3, pp. 20–32, 2000.

2. Yukio Horiguchi and Tetsuo Sawaragi, "Analyzing Task Morphologies for Naturalistic Task Sharing between Human Operator and Robot", *Journal of the Institute of Systems, Control and Information Engineers*, Vol. 13, No. 12, pp. 537–544, 2000. (in Japanese).

3. Yukio Horiguchi and Tetsuo Sawaragi, "Design of Mixed-Initiative Interactions between Human and Robot to Realize Shared Autonomies in Teleoperation Environment", *Transactions of the Society of Instrument and Control Engineers*, Vol. 38, No. 12, pp. 1097–1106, 2002. (in Japanese).

4. Tetsuo Sawaragi, Yukio Horiguchi and Motoi Ishizuka, "Modeling ecological expert: comparative analysis of human skill development with fuzzy controller", *Soft Computing*, Vol. 7, No. 3, pp. 140–147, 2003.

5. Yukio Horiguchi, Tetsuo Sawaragi and Masayuki Kuwatani, "Skill Analysis of Search Behavior via Remote-Controlled Robot from Ecological Perspective", accepted for publication, *Journal of Japan Society for Fuzzy Theory and Intelligent Informatics*. (in Japanese).

Book Chapters

6. Yukio Horiguchi and Tetsuo Sawaragi, "Co-Adaptation to Facilitate Naturalistic Human Involvement in Shared Control System", (eds.Tan, K.C., M. H. Lim, X. Yao, and L. Wang) *Recent Advances in Simulated Evolution and Learning*, World Scientific, pp. 769–788, 2004.

Refereed Conference Papers

7. Yukio Horiguchi, Tetsuo Sawaragi and Takayuki Shiose, "Character-Preserving and Diversity-Maintaining Strategy of Behavior-Based Robot under Different Training Environments", *Proceedings of 1998 Japan-U.S.A. Symposium on Flexible Automation*, pp. 761–767, 1998.

8. Yukio Horiguchi and Tetsuo Sawaragi, "Human-Robot Collaboration within A Virtual Space Using Behavioral Task-Morphologies", *Proceedings of 1999 IEEE International Conference on Systems, Man, and Cybernetics*, Vol. 1, pp. 756–761, 1999.

9. Yukio Horiguchi, Tetsuo Sawaragi and Go Akashi, "Naturalistic Human-Robot Collaboration Based upon Mixed-Initiative Interactions in Teleoperating Environment", *Proceedings of 2000 IEEE International Conference on Systems, Man, and Cybernetics*, pp. 876–881, 2000.

10. Tetsuo Sawaragi and Yukio Horiguchi, "Interfacing and Co-Adaptation between Interaction Loops of Human- and Machine-Autonomies Mediated by Ecological Task Environment", *Proceedings of The Sixth International Symposium on Artificial Life and Robotics*, pp. 415–420, 2001.

11. Yukio Horiguchi and Tetsuo Sawaragi, "Design of Shared Communicational Modality for Naturalistic Human-Robot Collaboration in Teleoperating Environment", *Proceedings of The Fifth International Conference on Knowledge-Based Intelligent Information Engineering Systems & Allied Technologies*, pp. 854–858, 2001.

12. Yukio Horiguchi and Tetsuo Sawaragi, "Naturalistic Human-Robot Collaboration Mediated by Shared Communicational Modality in Teleoperation System", *Proceedings of The Sixth International Computer Science Conference on Active Media Technology 2001*, pp. 24–35, 2001.

13. Yukio Horiguchi and Tetsuo Sawaragi, "Co-adaptation to Facilitate Feeling of Direct Involvement in Shared Autonomy System", *Proceedings of the 4th Asia-Pacific Conference on Simulated Evolution And Learning*, pp. 642–646, 2002.

14. Yukio Horiguchi and Tetsuo Sawaragi, "Toward Coordinated Decision between Human- and Machine-autonomies through Their Proactive Agency of Cognition", *Proceedings of SICE Annual Conference 2003*, pp. 2833–2838, 2003.

15. Yukio Horiguchi, Tetsuo Sawaragi and Masayuki Kuwatani, "Analysis of Search Activity via Remote Robot towards Natural and Effective Human-Machine

Collaboration Design", *Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems*, pp. 1077–1082, 2004.