Intelligence group report

G. Biswas *, T. Arai, M. Iskarous

Vanderbilt University, Computer Science, Box 1679, Station B, Nashville, TN 37235, USA

1. Introduction

The field of Biorobotics and service robotics in particular is making rapid advances [12]. The Intelligence group of the Biorobotics Workshop held in Tsukuba, Japan in May 1995, took on the role of surveying the state of the art of intelligent systems as they apply to service robotics, discussed the latest advances and needs for the next generation of these systems, and then charted out a roadmap for further development of intelligence in service robotics into the next decade. The group of researchers and practitioners who participated made brief presentations, and then discussed issues, challenges, and tasks to define the next generation of service robot systems. This report summarizes the different ideas within a cohesive framework, and then presents a set of grand challenges that are likely to govern research and development in the future.

Service robots are defined as adaptable, sensor-based mechatronic devices that perform useful services for humans. Kawamura et al. [9] classify service robots between industrial robots, such as welding and assembly machines, which operate in well-defined, pre-programmed, structured environments, and field robots, such as fully autonomous vehicles like the Mars Rover, which often have to operate in dynamic, unknown, and uncertain environments.

Unlike field robots, service robots are designed to perform tasks in specific environments. Examples of service robotics applications include assistance systems for the disabled and handicapped, hospital patient aides, office automation systems, and worker robots that assist humans in difficult and high precision tasks. The very nature of the applications and the important requirement of symbiosis with humans requires these robots to perform in a semi-autonomous and interactive framework. Furthermore, safety, efficiency, reliability, and the ability to communicate, understand, learn, and adapt are the key issues that govern the successful implementation of such systems.

Along with the sensory ability and control, intelligence, i.e., the ability to reason about, understand, and solve problems, plays a key role in the design and implementation of service robotics systems. A first step in the group discussion was to identify primary features for characterizing the concept of intelligence. These are discussed briefly below.

1.1. Shared understanding and mutual intelligibility

A key aspect for a group of cooperative agents to assist each other and successfully solve problems is through a shared understanding of a common goal structure. In [4,14], the concept of plans as a sequence of actions has been used as a mechanism for representing goal structures and prescribed solutions for achieving these goals; however, the notion of plans is often abstracted away from the situation or environment they need to be enacted. Shared understanding and mutual cooperation in service robotics is better achieved by looking at plans as situated actions [13]. In other words, plans should be looked upon as representation of actions that happen in the context of some ongoing activity based on circumstances and contexts.
that the problem solver is involved in. Cooperative agents can use goals and plans as a shared framework for achieving purposeful action.

1.2. Multiple and cooperative distributed problem solving architectures

The need for computationally manageable, robust, and reliable intelligent systems requires the use of multiple, distributed agents as opposed to centralized control. The traditional approach to decomposition was functional, based on a sequence of information processing tasks, such as breaking down a problem situation into perception, modelling, planning, task execution, and control functions. Brooks [1] and others propose a task-based decompositional approach. In task-based decomposition, the architecture of the robotic system is defined in terms of levels of competence. As an example, a mobile robot would develop competencies, such as, avoid bumping into objects, move around in an environment without collisions, create maps and plan routes, and react to dynamic changes in the environment while achieving goals [1]. Levels of competence involve multiple functional units, but each level is designed to be self-contained in its processing and communication channels. The processing capabilities of these units increase with the complexity of the task. To accommodate this, Brooks defines a layered subsumption architecture to implement levels of competence in a robotic system. Alternately, agent-based architectures (e.g. [8]) can also form the basis for designing task-oriented systems.

1.3. Human–robot communication paradigms

Traditional robotic applications have focused on language (speech and text) as a means of communication between humans and robots. Most robotic languages have had a narrow focus (set of specific commands), and therefore, first-order logic reasoning mechanisms have sufficed in specifying and understanding interactions [3]. More recently, the necessity for achieving not only human–robot, but also robot–robot communication in dynamic situations, and the availability of multiple sensors (sound, vision, tactile, etc.), has compounded the need for more innovative communication paradigms. Issues such as, how to handle communication breakdowns, who should be allowed to take charge in breakdown situations, and how to handle human emotions are also being discussed.

1.4. Working cooperatively in uncertain environments

As discussed, service robots need to operate in natural as opposed to structured (industrial) environments. These environments are dynamic, caused by the influence of phenomena outside the immediate environment, and the presence of other agents operating in the environment. In the absence of complete knowledge, intelligent systems need to incorporate uncertainty in their reasoning mechanisms and possess the capability for responding to unexpected changes in the environment during task execution activities. Probabilistic mechanisms for planning and task execution in uncertain environments have been proposed [5,10]. Reactive mechanisms are the second approach to deal with dynamic situations [2], but the real challenge is cooperative pooling of problem solving resources dynamically to reduce uncertainty and improve chances for success.

1.5. Dynamic interaction: Teaching, learning and evolution

Incomplete knowledge and information, and the complexity and dynamic nature of the tasks and environment makes it imperative for intelligent agents to possess capabilities for learning and improving performance with experience. A number of traditional learning paradigms: (i) learning by instruction, (ii) learning by doing, and (iii) learning to cooperate, directly apply to the human–robot symbiosis framework [4]. Given that the robot operates as a semi-autonomous agent in a service application, a natural question that arises is: Should the amount of autonomy given to a robot change as it becomes more experienced in task execution, and, if this is the case, how should it be controlled?

2. Summary of presentations

Within the framework described above, eight speakers made individual presentations on topics that
we divide into four primary categories: (i) problem solving architectures, (ii) planning and scheduling in complex, interactive, and uncertain problem solving environments, (iii) human–robot communication methodologies, and (iv) learning mechanisms for human–robot interactions. The rest of this section discusses the topics and the presentations.

2.1. Architectures

Prof. Arai’s presentation discussed dwarf intelligence, a system where a group of agents aware of a common goal or purpose, work together to achieve that goal. Agents reason at three levels: physical, geometrical, and informational. A virtual impedance methodology defines and governs the nature of the interactions between agents and how they achieve consensus in problem solving. Prof. Yuta’s talk was similar. He focused on how to put together sets of simple\(^1\) agents that combine to solve more complex tasks. The system control functions are implemented as a two-level architecture: behavior level and function level. All decision making is at the behavior level, which is then used to drive the modularly designed function-level system. A primary difference between dwarf intelligence and Prof. Yuta’s “Yamabiko” system is that decision making and high-level planning is centralized in the latter system. The laboratory at Tsukuba University has developed a number of these simple robotic systems, but a big research and development thrust now is how to make their computational architecture incremental.

Dr. Gomi took a different viewpoint in defining a behavior-based approach to designing the intelligence units of service robotics systems. The key issues in the behavior-based approach, an extension of subsumption architectures [1] discussed earlier, are the notions of emergent computation [7] and evolutionary robotics [6]. The key idea behind these concepts is non-Cartesian robotic systems, i.e., systems which do not commit significant computational resources to modelling, model analysis, computation, planning, and centralized control. The future plans are to develop a multi-tasking, embedded subsumption architecture with action selection dynamics [11] as an operating control system for autonomous mobile robot systems.

There was some debate within the group about the exact nature of non-Cartesian decomposition and its role in the design of next generation robotics systems. No clear consensus was achieved on the superiority of this computational architecture over other distributed agent-based architectures.

2.2. Planning and scheduling

Prof. Biswas presented a probabilistic framework for representing and reasoning about uncertainty during action selection for a service robotics application – feeding a handicapped person. This application is interaction intensive with extensive communication occurring between humans and robots to achieve goal definition, goal refinement, and goal modification during task execution. Uncertainty arises for several reasons: (i) the agent has incomplete knowledge about the environment and the success of actions, (ii) other agents can change the state of the environment dynamically, and (iii) the user who is being serviced by the robot may change his goals, e.g., while being fed spaghetti the user may request a drink of water. A spreading activation computational mechanism was implemented in a decision-theoretic framework for choosing the “best”\(^2\) action in a given situation. The methodology’s anytime planning characteristic and the ability to plan, act, and react in uncertain situations was demonstrated by a number of simulated examples.

Prof. Ueno discussed a model-based vision and intelligent scheduling system for an autonomous robot arm for grasping, carrying, and placing operations. The design of the vision system, the arm controller, and the reasoning mechanisms for the intelligent scheduler are based on models of cognitive psychology, the goal being to emulate human arm movements. The vision system relies on 3-D world models and the interactive scheduler uses a pre-defined knowledge base to generate a sequence of actions for achieving the goal. This process computes the desired goal state as a mental picture, and then reasons from differences in the current world state and desired goal state to find suitable actions.

\(^1\) From a hardware, software, and control viewpoint.

\(^2\) “best” has been defined as the action that is most likely to succeed in achieving desired goals.
A primary difference between the two approaches discussed above is that the Prof. Ueno methodology assumes static world models (and, therefore, a static knowledge base), but the Prof. Biswas methodology allows for incomplete knowledge. Failure to achieve a desired goal or subgoal may result in: (a) re-doing an action, or (b) picking an alternate action. In either case, the conditional probability between actions and their conditions are updated to refine the knowledge base. Both these methods can be contrasted to the non-Cartesian methodology proposed by Dr. Gomi. It may be interesting to see the evolution of reasoning schemes based on decision-theoretic rational analysis versus the pure behavior-based schemes that underlie the subsumption architecture approach.

2.3. Human–robot interaction

Dr. Sato presented the model of a Robotic room (a human–robot symbiosis system). The purpose of this room is to service a disabled or sick human by supporting his or her activities in a useful, reliable, and friendly manner. He outlined key functions to achieve symbiosis: (i) the ability to share physical space, (ii) the ability to communicate and respond to a human need in real time, (iii) the ability to share mental activities in the form of understanding and communicating intentions and emotions, and (iv) the ability to perform physical tasks together. He also discussed the necessary system components: (i) a multi-sensory system in the environment, (ii) bilateral imaging devices, (iii) dual communication loops with the ability to process behaviors, (iv) long reach manipulators, and (v) real-time communication systems. Dr. Sato’s presentation dealt mostly with conceptual design issues, however, the scenarios presented, allowed the group to focus on a set of key issues that would have to be dealt with in human–robot symbiosis.

Dr. Iskarous presentation focused more on the imprecise nature of natural language, and the necessity for fuzzy modelling of linguistic knowledge to achieve effective and user-friendly human–robot communication. His work focused on a neuro-fuzzy learning and reasoning scheme that is incremental, and can operate in real time. Its primary application in service robotics would be in modelling reflex behavior of humans in specific situations (e.g., arm motions), and then adjusting the robotic systems control parameters to provide support and the right response.

Some of the other talks also discussed human–robot interactions. Prof. Ueno used a simple natural language communication mechanism, where commands to the robotic system were interpreted in terms of task action verbs and other objects present in the environment. The human–robot communication mechanisms described by Profs. Yuta and Biswas were also action-based. Prof. Arai defined a more extensive framework which included physical, geometrical, and informational as three different dimensions for communication and interaction. There was a lot of discussion on what is the appropriate set of parameters to define and circumscribe human–robot interaction. These are discussed in Section 3.

2.4. Learning mechanisms

Dr. Klopf’s presentation centered around the concept of reinforcement learning based on a model of natural intelligence, i.e., real-time, goal-seeking interactions between a biological system and its environment. This model closely resembles nervous system function. It is supported by studies on animal learning psychology that were conducted in the 1940s and 1950s. The learning model has two phases. The first phase involves the acquisition of basic emotions, such as hope, fear, relief, disappointment, and anger. These become the reinforcement centers. In the second phase, appropriate motor responses and behaviors are learned guided by emotional response. Dr. Klopf’s implementation of this system as Associative Control Process (ACP) networks has been successfully tested in a number of applications.

This work brought out an underlying basis for human behavior based robotic systems. The strong underpinning and connections to the behavior-based subsumption architecture approach should be noted. A unifying conjecture that may form the basis of human–robot interaction is that the reinforcement centers of robotic systems can be conditioned by human users so that subsumption architecture based robotic systems can operate in a cooperative or symbiotic mode rather than as independent autonomous agents.
3. Discussion issues

After the individual presentations, a set of relevant topics were selected for further discussion. They are summarized below.

3.1. Role of intelligence in human–robot symbiosis

The first question this group addressed was what is intelligence? Not unexpectedly, the answer to this question is elusive, but reasonable discussion could take place if one focused on particular contexts and applications; therefore, the question was changed to, What is the role of intelligence in human–robot symbiosis? Human–robot symbiosis was characterized as the coexistence and cooperation among humans and robots to achieve common goals using intelligent interfaces.

First, a primary set of features were identified that capture the spirit of symbiosis.

- **Mutual benefit**: That robots should benefit humans in a service robotics situation was taken for granted, but should true symbiosis also imply that robots benefit from interactions with humans? In the case of robots, how should benefits be defined?

Would the education and learning experiences that an interacting human provide the robot to help its intelligence evolve resulting in improved emergent behavior be considered a benefit? The general consensus in the group was yes, but the support was not very emphatic. Also, when multiple robots operate together, their mutual benefit to each other, and the evolution of the group as a whole need to be considered.

- **Emerging behavior**: For robotic systems this is primarily at three levels: learning, adaptation, and evolution.

- **Social behavior**: The question about friendly interaction was raised. What defines friendly social behavior? Can it be characterized beyond a master–slave relation between humans and robots? Adaptation to humans and the environment can definitely be classified as desirable social behavior. However, would a robotic system that is learning and evolving be considered friendly by humans or be perceived as a threat? A changing system that does the same task differently a second time may confuse the human being serviced. The conclusion was that a number of social factors may need to be introduced into a robot systems decision making processes. It is important that the robot accommodate a human’s requests and desires to be considered friendly and useful.

- **Robust interaction**: Robotic systems need to understand human directives and needs, and perform to expectations so as not to frustrate the human user.

3.2. Architecture for intelligent systems

A wide spectrum of architectures exist for intelligent systems. The two ends of the spectrum are the functional decomposition and the behavior-based architectures (see Fig. 1). At the heart of the debate between the two architectures was whether problem solving architecture design should follow a Cartesian (i.e., functional decomposition) or non-Cartesian (e.g., subsumption) approach. Non-Cartesian architectures are governed by their simplicity. They can be built by

![Diagram of computational architectures]

Fig. 1. Spectrum of computational architectures.
composition of a set of Sense & Act modules. Complex behaviors can be obtained by building up levels of competence. However, to date, these architectures have demonstrated fairly simple autonomous behavior, and it has not been shown how easily they may scale up to demonstrate complex behaviors and problem-solving activity. On the other hand, the traditional functional decomposition approach has been applied in the design and implementation of a number of complex systems. Prof. Yuta's view was that centralized hierarchical control was easier to implement than distributed control. He recommended behavior-based centralized control. Dr. Gomi made an important point that the Cartesian systems are more inflexible; once designed their processing modules become rather inflexible.

The general consensus among the group was that both architectures could coexist at different levels of intelligence. Behavior-based architectures are more suitable for low-level interaction between sensors and actuators, whereas, functional architectures may be more useful for more complex goal-driven tasks. Looking back at past systems, this may be justified, but it was not clear that this should be the roadmap for the future.

3.3. Human–robot symbiosis

The nature of human–robot symbiosis was investigated further. It was decided that symbiosis should start with co-existence which takes on three forms: (i) physical coexistence – humans and robots need to live in and operate in the same space without hurting each other or causing undue interference, (ii) functional coexistence – humans and robots have to cooperate and work together to achieve common goals; this requires a good understanding of each other's roles, and the ability to mutually develop, refine, and modify goals in different problem situations, and (iii) physiological coexistence – in serving the disabled, handicapped, or the sick, the robot is going to be in close proximity of the human. In order to ensure human safety, it is essential that the robot has good knowledge of human physiology.

A fourth point debated was emotional coexistence, which a number of participants thought was equally important. Should a robotic system be capable of understanding human emotions, and if so, does it need to be trained to react differently to different human emotional states. Some of it can be linked back to the reinforcement learning paradigm, but, this is largely a new issue, that was listed as an important technology gap that needed to be addressed.

4. Technology gap

Several items were discussed and considered to be technological gaps in achieving intelligent systems. These items are as follows:
- Conventional concerns.
- Newly listed concerns that seemed to arise from specific discussions at the Workshop.

4.1. Conventional topics

Conventional concerns have been at the heart of research in AI and computational intelligence for some time.
- Computational architectures.
- Sensors and integration or synthesis of information from multiple sensors.
- Communication systems, hardware issues (e.g., bandwidth) and software issues (e.g., protocols).
- Conventional interaction mechanisms, e.g., natural language understanding, speech processing, and tactile sensing.
- Other interaction mechanisms, such as gesture and motion understanding.
- Shared understanding and situated actions, and
- Learning and adaptability.

4.2. Newer topics

These refer to emerging research areas, and issues that especially need to be addressed to achieve human–robot symbiosis. This category includes the following.
- Extensions of conventional first-order logic to incorporate complex reasoning issues and human emotions.
Table 1
Desired forms of communication among agents

<table>
<thead>
<tr>
<th></th>
<th>Human to Robot</th>
<th>Robot to Human</th>
<th>Robot to Robot</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Send</td>
<td>Receive</td>
<td>Send</td>
</tr>
<tr>
<td>Rational</td>
<td>NL</td>
<td>NL</td>
<td>NL</td>
</tr>
<tr>
<td></td>
<td>Gesture</td>
<td>Sound</td>
<td>Motion</td>
</tr>
<tr>
<td></td>
<td>Visual</td>
<td>Visual</td>
<td></td>
</tr>
<tr>
<td>Emotional</td>
<td>Gesture</td>
<td>Visual</td>
<td>NL</td>
</tr>
<tr>
<td></td>
<td>Tone</td>
<td>Sound</td>
<td>Motion</td>
</tr>
</tbody>
</table>

Note: NL, Natural Language.

- Recognition, understanding, and the ability to react to human emotions.
- Better circumscribe the concept of human–robot symbiosis.

5. Roadmap

A roadmap for intelligence in service robotics and human–robot symbiosis encompasses multiple dimensions: computational architectures, multi-dimensional sensing and integration, situated planning and reacting, efficient task execution, learning, adaptation and evolution, all of which have been discussed in some detail in the earlier sections. A key research issue needing significant progress is the area of communication among agents: human to robot, robot to human, and robot to robot. Communication has to be studied in three forms: the content, the media, and the hardware. Table 1 summarizes the form of communications, rational and emotional, that need to be developed among the different agents. The first column for each category indicates the forms that the primary agent would like to communicate (send) and the second column describes the forms that the agent would like to receive information (receive).

In addition, a roadmap for the future needs to develop well-defined standards and performance and evaluation measures for (i) efficiency, (ii) friendliness, and (iii) robustness.

References


6. List of Group Participants

Group Leaders:

Prof. T. Arai, arai@prince.pe.u-tokyo.ac.jp
University of Tokyo, Japan.

Prof. G. Biswas, biswas@vuse.vanderbilt.edu
Vanderbilt University, Nashville, TN, USA.

Participants:

Dr. M. Iskarous, moenes@C-Cube.com
C-Cube Microsystems, Milpitas, CA, USA.

Prof. S. Yuta, yuta@is.tsukuba.ac.jp
University of Tsukuba, Japan.

Dr. A. H. Klopf, klopfah@aa.wpafb.af.mil
Wright Labs, USAF, USA.

Dr. T. Davis, daviste@emh.yokota.af.mil
USAF AFOSR/AOARD, Tokyo, Japan

Mr. T. Gomi, 71021.2755@compuserve.com
Applied AI Systems, Kanata, Ontario, Canada.

Mr. Y. Nishida, nishida@lssl.rcast.u-tokyo.ac.jp
The University of Tokyo, Japan.

Prof. T. Sato, tomo@lssl.rcast.u-tokyo.ac.jp
The University of Tokyo, Japan.

Prof. Ueno, ueno@ailab.k.dendai.ac.jp
Tokyo Denki University, Japan.

Dr. T. Ogasawara, ogasawara@ctl.go.jp
Electrotechnical Laboratory, Tsukuba, Japan.

Mr. M. Kawabe, kawa@yaskawa.co.jp
Tsukuba Research Lab, Yasakawa Electric Corp.,
Tsukuba, Japan

Prof. Y. Cho, eyj@amadeus.kist.re.kr
Korea Institute of Science & Technology, Seoul, Korea.

Mr. Y. Ha, hys@roboken.is.tsukuba.ac.jp
University of Tsukuba, Japan.

Prof. Y. Saito, saito@ccs.dendai.ac.jp
Tokyo Denki University, Japan.

Dr. K. Homma, homma@mel.go.jp
MITI, Tsukuba, Japan.

Dr. M. Ejiri, ejiri@crl.hitachi.co.jp
Central Research Laboratory, Hitachi Ltd. Tokyo, Japan.