June 1993

GRASP News: Volume 9, Number 1

Faculty & Graduate Students
University of Pennsylvania

University of Pennsylvania Department of Computer and Information Science Technical Report No. MS-CIS-93-58.

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Abstract

The past year at the GRASP Lab has been an exciting and productive period. As always, innovation and technical advancement arising from past research has lead to unexpected questions and fertile areas for new research. New robots, new mobile platforms, new sensors and cameras, and new personnel have all contributed to the breathtaking pace of the change. Perhaps the most significant change is the trend towards multi-disciplinary projects, most notable the multi-agent project (see inside for details on this, and all the other new and on-going projects). This issue of GRASP News covers the developments for the year 1992 and the first quarter of 1993.

Comments

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GRASP LAB 349

Faculty & Graduate Students

University of Pennsylvania
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Computer and Information Science Department
Philadelphia, PA 19104-6389

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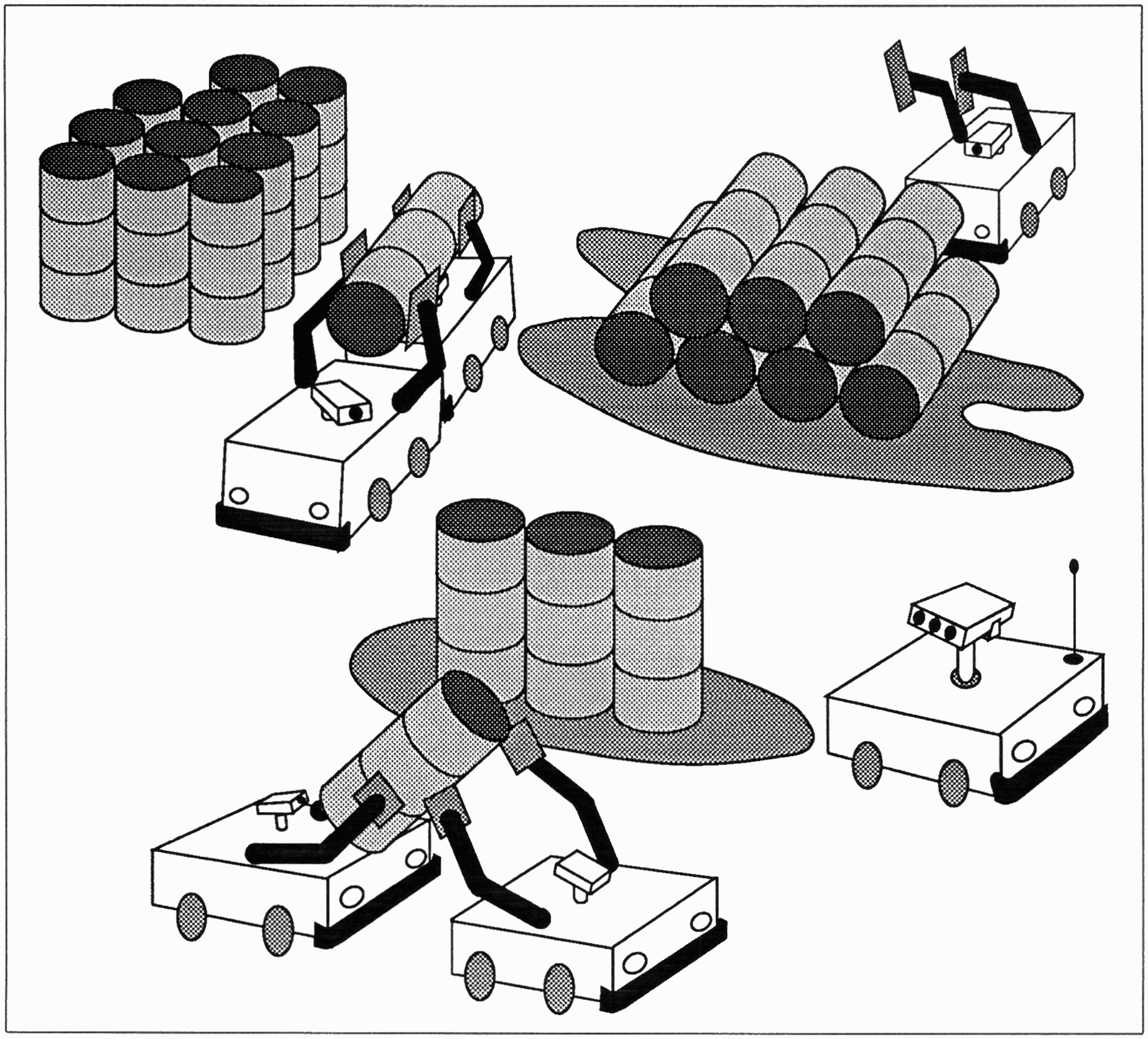
GRASP News

Volume 9, Number 1 Spring 1993



UNIVERSITY OF PENNSYLVANIA

A Report of the General Robotics and Active Sensory Perception Laboratory

GRASP Laboratory

GRASP News

Volume 9, Number 1 Spring 1993

General Robotics and Active Sensory Perception (GRASP) Laboratory
University of Pennsylvania
Philadelphia, PA 19104-6228

GRASP News[1] is published by the Department of Computer and Information Science, University of Pennsylvania, Philadelphia, Pennsylvania 19104-6389. This edition of the *GRASP News* was edited by Stamps Howard and Yoshio Yamamoto.

Cover sketch of "multiple agents working in a coordinated environment" by Yoshio Yamamoto, adapted from the original sketch by Eric Paljug. The cover layout was designed by Yoshio Yamamoto. The title logo on the front cover was designed by Tom Lindsay.

Grasp Laboratory research reported in this document was supported by Navy Grant N00014-92-J-1647; AFOSR Grants 88-0244 and 88-0296; Army/DAAL 03-89-C-0031PRI; NSF Grants CISE/CDA 88-22719, IRI 89-06770, ASC 91-0813, MSS-91-57156, and CISE/CDA 90-2253; NATO Grant No. 0224/85; A. I. duPont Institute, Bartrett Technology Inc., Du Pont Corporation, and General Motors.

GRASP News was typeset using Donald Knuth's TEX typesetting system and Leslie Lamport's LATEX macro package running under SunOS Release 4.1. Printing was done on an Apple Laserwriter.

Additional copies of *GRASP News* can be ordered from the Department of Computer and Information Science as Technical Report MS-CIS-93-58, GRASP LAB 349.

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1 Forum

Editors' Foreword

The past year at the GRASP Lab has been an exciting and productive period. As always, innovation and technical advancement arising from past research has lead to unexpected questions and fertile areas for new research. New robots, new mobile platforms, new sensors and cameras, and new personnel have all contributed to the breathtaking pace of the change. Perhaps the most significant change is the trend towards multi-disciplinary projects, most notably the multi-agent project (see inside for details on this, and all the other new and on-going project). This issue of GRASP News covers the developments for the year 1992 and the first quarter of 1993.

We would like to take this opportunity to mention some of our colleagues who have graduated since the last *GRASP News* was published.

Dr. Gerda Kamberova is a PostDoctoral Fellow with the Mechanical Engineering Department at Rice University, currently involved in a project of fuzzy logic based tracker. **Dr. Robert Kennedy** presently holds a position as a quantitative research analyst at Susquehanna Investment Group, Philadelphia PA, specializing in the valuation of derivative securities. **Dr. Tom Lindsay** is currently working at the Space Systems Division of Rockwell International (Downey, California), Projects include dynamic modelling of robotic mechanisms, robotic equipment integration and control, and technical support for new business pursuits. **Dr. Eric Paljug** joined the Man-Machine Systems Group of the Jet Propulsion Laboratory where he is researching control system design, computing, and electronics for advanced teleoperation. **Dr. Marcos Salganicoff** is currently an NSF Postdoctoral Associate here at GRASP Lab. **Dr. Yintien Wang** is presently an Assistant Professor of the Department of Mechanical Engineering at Tamkang University in Taiwan.

Chris Gerdes, who graduated with an M.S. last summer, is presently a PhD candidate at the Department of Mechanical Engineering, University of California, Berkeley. **Tom Sugar**, who also graduated with an M.S. last summer, is currently with Gore Co.

Dr. Ealan Henis, who held a postdoctoral position at the University until December 1992, joined the Information Principles Laboratory of AT&T Bell Laboratories in Murray-Hill, NJ, as member of staff.

We wish a fond farewell to all these former fellow researchers, as we strive to extend the research they began and expand upon their results.

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Director's Note

This issue of GRASP news celebrates the 10th anniversary of the GRASP laboratory. The establishment of the GRASP lab never was a formal event, hence there is no precise date of its birth, but in 1982 a group of faculty (Sam Goldwasser, Insup Lee and myself) realized that we have some common interests which would justify sharing a laboratory. It was around the same time when I began to formulate the ideas on Active Perception, hence the name of the laboratory: General Robotics and Active Sensory Perception. We also have great pleasure in celebrating the tenure of Peter Allen, at Columbia University, who was the first graduate from the GRASP lab. Since then we have a great family of GRASPEES all over the world. Jumping to the present, the GRASP lab faculty has two new additions: Profs. Eero Simoncelli (formerly from MIT) who joined in January 93 and Dimitri Metaxas (formerly from Toronto) who joined in September 92. This brings the number of faculty in the GRASP lab to *eight*. Our current research topics vary, based on individual faculty interests and we have a few shared projects. One is on *Cooperative Agents*, where agents are machines and people. The other projects are on *the Reverse Engineering*, which consists of simulation and testing of traditional manufacturing processes of mechanical assemblies as well as more non-traditional processes such as spraying technologies, textile manufacturing and so on. These projects include many other interests and capabilities of the GRASPEES such as physics based vision, shape recognition, active focus of attention, studies of functionality of objects, teleoperation, and many more.

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2 Feature Article

Cooperative Agents: Machines and Humans

by
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in collaboration with
Vijay Kumar, Max Mintz, Richard Paul, and Xiaoping Yun

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2.1 Introduction and Motivation

Why has robotics failed? There are several reasons, namely that robots are stupid, and are neither fast nor cost effective. Robots are stupid primarily because they are typically sensory deprived; hence, they work in open loops with very limited intelligence. They are slow because they are heavy; hence, they have large inertia. Further, robots are heavy because of the required payload which determines the weight of subsequent actuators.

What is the solution? For more intelligent robots we need: a) a large variety of sensors that are both complementary and redundant; b) flexible processing of sensory data, i.e. flexible data reduction mechanisms; c) flexible sensory based control (force control in particular); d) strategies for sensory placement; and e) modeling capabilities of sensors, manipulators, the world and the task. For faster and more efficient intelligent robots we need more agile and lighter mechanisms. Our answer is *Distributed Multiagents*, where each agent is lighter and more agile. Multiagents not only distribute the payload, but also the subtasks.

Why is distributed robotics not yet a common technology? The reason is a lack of understanding: a) communication; b) coordination and/or cooperation of sensors, manipulators and agents in general; and c) distributed planning. In response to such needs, our research concentrates on the problem of *cooperation*. In what follows we shall define the process of cooperation and then show different instances of cooperation between sensors, manipulators, agents and humans.

2.2 Cooperation: What is it?

Cooperation is a process of taking different observations and information from the *same world* (our world includes the agents) and combining it in such a way that the process achieves a *common task.* Cooperation is also a process which requires agents to collectively distribute *task-related actions* amongst themselves in order to achieve the *top level task.*

For the purposes of our research the following assumptions are made: a) agents are either Mobile Observers, Mobile Manipulators or Humans; b) all robotic agents live in the same world/environment; c) each agent knows its role in the *top level task*; d) agents have capabilities of observation and communication if needed; e) Observer Agents cannot manipulate, but Mobile Agents can observe; and f) the initial position of each agent is predetermined and they all carry out the same task.

We shall consider cooperation on the sensory level, the manipulatory level, the mobile observer level, and the agent-agent cooperation level.

2.3 Cooperation at the Sensory Level

2.3.1 Foundations for Sensory Fusion

Multisensory information obtained by one or more agents is combined (fused) in a common framework. There are two important cases to distinguish:

1. Homogeneous Sensor Fusion: the homogeneous case refers to the circumstance where the sensed information has a common character, e.g. multiple measurements of the spatial position of one or more targets. Here, the sensors need *not* be homogeneous with respect to the physical method for spatial position determination, e.g. ultrasound and vision.

2. Heterogeneous Sensor Fusion: the heterogeneous case refers to the circumstance where the sensed information has multiple characteristics, e.g. object shape and object color. The data need *not* come from separate physical sensors — but rather separate logical sensors. Here, sensor fusion has a complementary role in the combination of heterogeneous information.

For our sensor fusion methodology we (Mintz, McKendall, Kamberova and Mandelbaum, 1992) have developed a very general confidence set-based approach for robust sensor fusion which accounts for: a) significant uncertainty in sensor noise distributions (shown in Figure 1); b) set-valued uncertainty in sensor position (shown in Figure 2); and c) geometric constraints attached to the problem domain. The method provides tight probabilistic measures of confidence on fusion inference *without* requiring insupportable assumptions about sensor noise behavior or *a priori* probabilistic models of the world. Moreover, the theory includes a means to obtain cooperation between independent sensor platforms in gathering new and maximally informative sensor data.

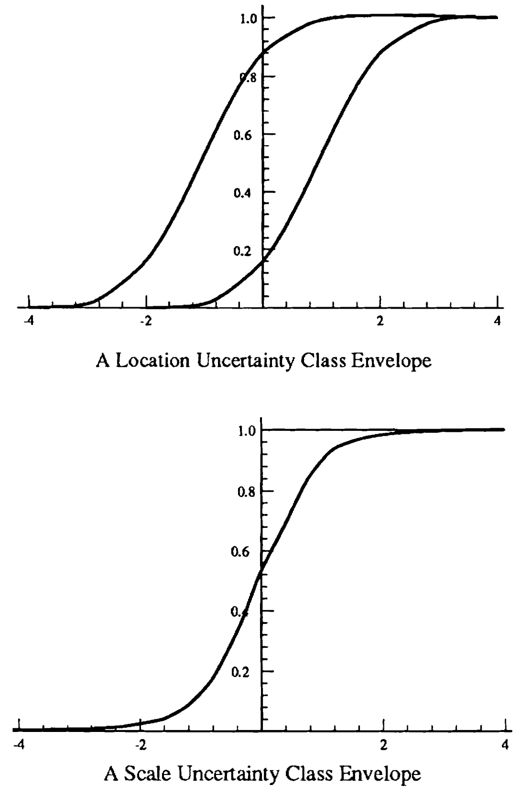


Figure 1: Examples of Sensor Noise Distribution — Uncertainty Classes $\mathcal{F}$

□ We address homogeneous and heterogeneous multisensor fusion by means of Robust Fixed-Geometry Confidence Sets

□ Sensor Measurements: $Z = \theta + V$.

□ *A Priori* Knowledge from Physical Constraints or Previous Sensor Data: $\theta \in \Omega$.

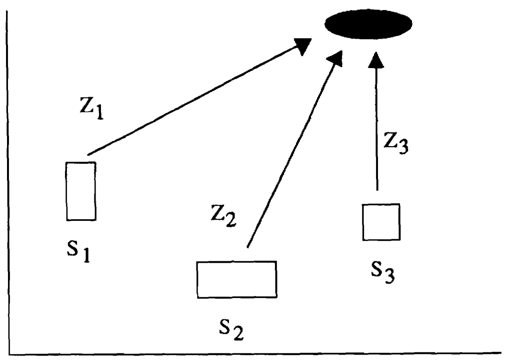
□ V Sensor Noise with CDF $F \in \mathcal{F}$ — A Given Uncertainty Class.

□ A Set $C(Z)$ with Fixed Geometry (Rectangle, Ellipse, etc. with given parameters) is a Robust Fixed-Geometry Confidence Set if it solves the following Max-Min Problem:

$$\max_{C} \min_{\theta\in\Omega, F\in\mathcal{F}} P[C(Z) \ni \theta].$$

Figure 2: Multisensor Fusion via Robust Fixed-Geometry Confidence Sets

Homogeneous Multisensor Fusion of Position Data



Multisensor Fusion of Position Data
With Sensor Location Uncertainty

Sensor Data:

$$Z_k = \theta_k + V_k, k = 1, 2, 3$$
$$\theta_k \in \Omega, k = 1, 2, 3$$

Consistency Test:

Does $\theta_1 = \theta_2 = \theta_3$?

Figure 3: Homogeneous Multisensor Fusion

The Homogeneous Multisensor Fusion of Position Data is depicted in Figure 3; Heterogeneous Multisensory Fusion is depicted in Figure 4.

2.3.2 Disambiguation of Reflectance Measurements

Here the problem is to understand reflectance measurements in terms highlights, interreflections, shading, shadows, transparency and albedo. Since the measurement is an algebraic combination of the above components, the task is to decompose the measurement(s) into their respective components. But first a few definitions (see Table 1 and Figure 5).

The Geometrical Model

In modeling the light reflection from solid surfaces, the bidirectional reflectance distribution function (BRDF) proposed by Nicodemus et. al. is a very general concept and thus widely accepted for use in computer vision. In this section, geometric representation of light

Sensor Data:

$$Z_k = \theta_k + V_k, k = 1, 2, 3$$
$$\theta_k \in \Omega_k, k = 1, 2, 3$$

Inference Issue 1:

Does $(\theta_1, \theta_2, \theta_3) \in \Gamma \subset \Omega_1 \times \Omega_2 \times \Omega_3$?

Inference Issue 2:

Find a Set-Valued Estimate $S(Z_1, Z_2, Z_3)$ of size $e(\alpha)$ which contains $(\theta_1, \theta_2, \theta_3)$ with probability at least $1 - \alpha$.

Figure 4: Heterogeneous Multisensor Fusion

Symbol	*Symbol Definition*	*Unit*
Φ	Radiant flux	W
$I = d\Phi/d\omega$	Radiant intensity	$W \cdot sr^{-1}$
$E = d\Phi/dA$	Irradiance	$W \cdot m^{-2}$
$M = d\Phi/dA$	Radiant Exitance	$W \cdot m^{-2}$
$L = d\Phi/(dA \cos\theta d\omega)$	Radiance	$W \cdot m^{-2} \cdot sr^{-1}$
ω	Solid angle	sr
$\Omega = d\omega \cos\theta$	Projected solid angle	sr
θ	viewing angle w.r.t. surface normal	rad
A	surface area	m^2
f_r	BRDF	sr^{-1}

Table 1: Radiometric Definitions

and reflection is briefly introduced with radiometric concepts.

The BRDF is defined as the ratio of the reflected radiance dL_r in the viewing direction to the irradiance dE_i in the direction of incident light, i.e.,

$$f_r(\theta_i, \phi_i; \theta_r, \phi_r) = \frac{dL_r(\theta_r, \phi_r; \theta_i, \phi_i; E_i)}{dE_i(\theta_i, \phi_i)} = \frac{d^2\Phi_r/d\Omega_r}{d\Phi_i}.$$

The definition of the BRDF f_r can be extended by including the spectral dimension as

$$f_r(\theta_i, \phi_i; \theta_r, \phi_r; \lambda) = \frac{dL_r(\theta_r, \phi_r; \theta_i, \phi_i; \lambda; E_i)}{dE_i(\theta_i, \phi_i; \lambda)} = \frac{d^2\Phi_r/d\Omega_r}{d\Phi_i}.$$

When the spectral variable λ and the geometrical variable are independent, they can be separable. There has been a report that the spectral composition of Lambertian reflection

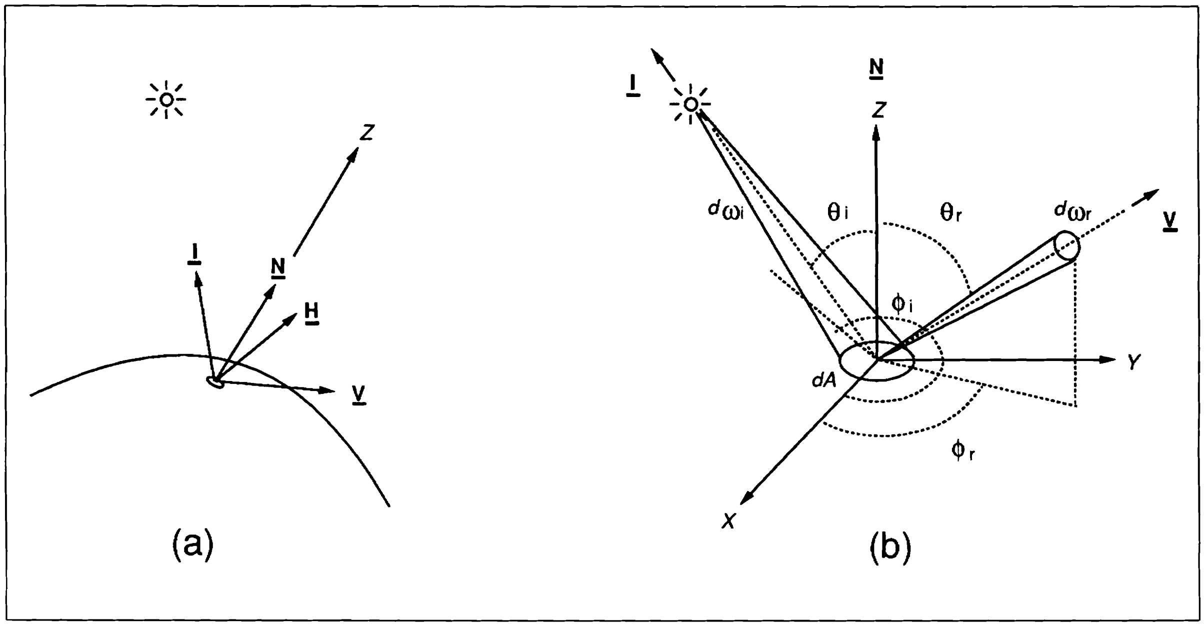


Figure 5: Local geometry of incident and reflected rays

slightly changes when the incident light direction approaches 90^o with respect to surface normal (glancing incidence). However this effect is small even at near the glancing incidence of light, and thus can be neglected in the model.

By separating the variables and including spectral reflectances, the BRDF can be written as

$$f_r(\theta_i, \phi_i; \theta_r, \phi_r; \lambda) = \rho_S(\lambda) g_S(\theta_i, \phi_i; \theta_r, \phi_r) + \rho_B(\lambda) g_B(\theta_i, \phi_i),$$

where $\rho_S(\lambda)$ and $\rho_B(\lambda)$ are the specular and the Lambertian reflectances, i.e. Fresnel reflectance and albedo, respectively. Note that g_B is 0 for metals, and for dielectrics g_B is independent of the viewing angle (θ_r, ϕ_r). Since the geometrical weighting has different mechanisms for specular and Lambertian reflections, they are separately included in the BRDF.

From the definition of BRDF, the scene radiance from an object point (small patch) is given as

$$\begin{aligned} L_r(\lambda) &= \rho_S(\lambda) \int_{\omega_i} g_S(\theta_i, \phi_i; \theta_r, \phi_r) L_i(\theta_i, \phi_i; \lambda) \cos\theta_i d\omega_i \\ &+ \rho_B(\lambda) \int_{\omega_i} g_B(\theta_i, \phi_i) L_i(\theta_i, \phi_i; \lambda) \cos\theta_i d\omega_i \\ &= e_{GS}(\theta_r, \phi_r; \lambda) \rho_S(\lambda) + e_{GB}(\lambda) \rho_B(\lambda), \end{aligned}$$

where e_{GS} and e_{GB} are the geometrically weighted and integrated illumination from different directions for the specular and the Lambertian reflection, respectively. The observation of the specular reflection is highly dependent both on the viewer and on the illumination directions, while the body reflection depends only on the illumination direction. In general, the illumination source $L_i(\theta_i, \phi_i; \lambda)$ can be geometrically extended with spectral variation, and a surface patch receives different illumination color from different illumination directions (θ_i, ϕ_i).

When the spectral composition of the light source does not vary depending on the direction (θ_i, ϕ_i), the geometrical variables and the spectral composition of the incident light are separable, i.e.,

$$L_i(\theta_i, \phi_i; \lambda) = e(\lambda) L_i(\theta_i, \phi_i),$$

where $e(\lambda)$ is a normalized spectral distribution function for illumination.

The Spectral Model

From the definition of BRDF, the scene radiance is given as

$$\begin{aligned} L_r(\lambda) &= e(\lambda)\rho_S(\lambda) \int_{w_i} g_S(\theta_i, \phi_i; \theta_r, \phi_r) L_i(\theta_i, \phi_i) \cos\theta_i d\omega_i \\ &+ e(\lambda)\rho_B(\lambda) \int_{w_i} g_B(\theta_i, \phi_i) L_i(\theta_i, \phi_i) \cos\theta_i d\omega_i \\ &= e(\lambda)[\rho_S(\lambda) G_S(\theta_r, \phi_r) + \rho_B(\lambda) G_B] \\ &= e(\lambda) s(\lambda), \end{aligned}$$

where $G_S(\theta_r, \phi_r)$ and G_B are the pure geometrical factors which are independent of spectral information. The surface reflection

$$s(\lambda) = \rho_S(\lambda) G_S(\theta_r, \phi_r) + \rho_B(\lambda) G_B$$

is the linear combination of specular and Lambertian reflections with the different geometrical weighting factors. A special case of the separability of λ and (θ_i, ϕ_i) is a scene under a collimated source. When collimated scene illumination is given by

$$L_i(\theta_i, \phi_i; \lambda) = e(\lambda)\delta(\theta_i - \theta_I)\delta(\phi_i - \phi_I)/\sin\theta,$$

where (θ_I, ϕ_I) is the direction of the collimated illumination, the radiance is

$$L_r(\lambda) = e(\lambda)[s_S(\lambda) g_S(\theta_I, \phi_I; \theta_r, \phi_r)\cos\theta_I + s_B(\lambda) g_B(\theta_I, \phi_I)\cos\theta_I].$$

It is only when the illumination is spectrally uniform regardless of directions, that the scene radiance L_r is given as the product of the scene illumination $e(\lambda)$ and the surface reflection $s(\lambda)$

As we can see from the above equations, for every point (x, y) in an image measurement $L_r(x)$ is a linear combination of nonlinear functions of 10 or more variables. It is clear that if we just measure the reflectance the problem is underdetermined; hence, we need either more measurements and/or more assumptions.

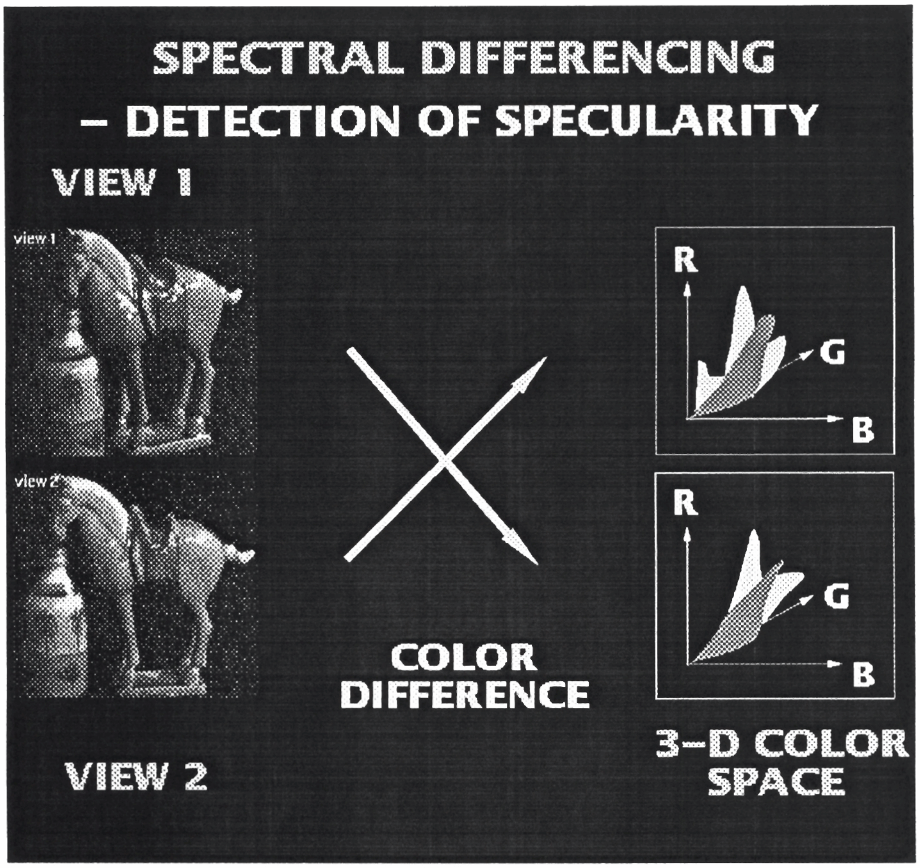


Figure 6: Spectral Differencing: Detection of Specularity

I would like to argue that this decomposition process is a cooperation between how many measurements one takes from the spectral vs. spatio-temporal domains. The example in Figure 6 demonstrates the representation (histogram) of two views in R, G, B space. The differencing shown in Figure 7 allows us to detect specularity in the situation of surfaces with varied albedos. (For more details, see Sang Wook Lee's Ph.D. thesis.)

2.4 Cooperation on the Manipulatory Level

This work, based on the research of Profs. Yun and Kumar and their students Stamps Howard, Eric Paljug, Nilanjan Sarkar, Chau-Chang Wang and Yoshio Yamamoto, yields two useful examples: a) coordination of two arms (see Figures 8 and 9); and b) coordination of two mobile manipulators (see Figures 10-13). The common task is to perform one or a series of actions, such as grasping, holding and/or moving an object.

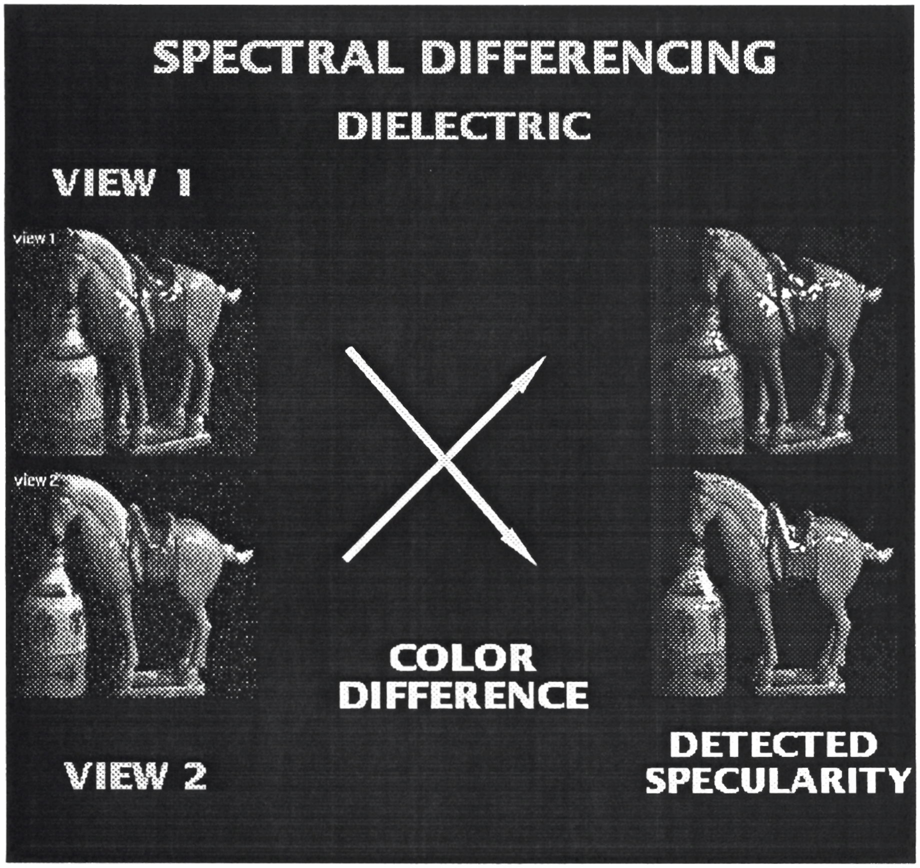
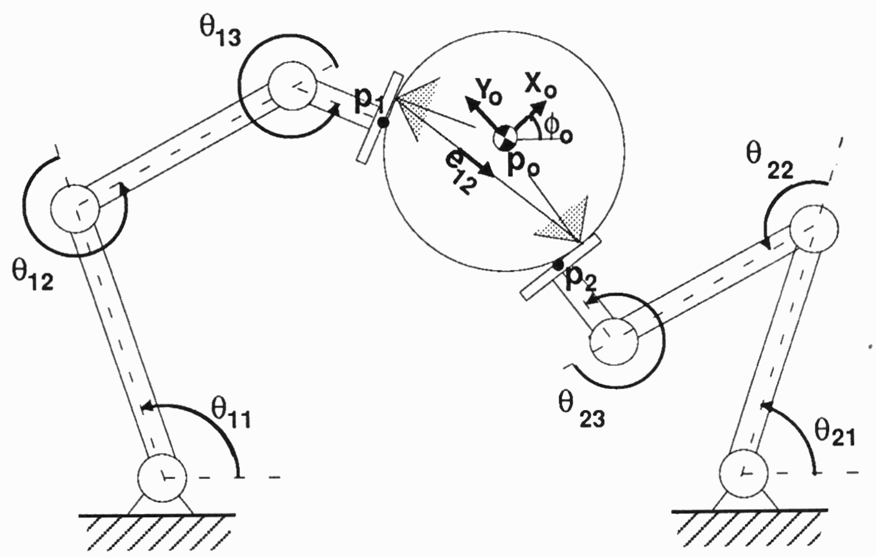


Figure 7: Spectral Differencing: Dielectric

2.5 Mobile Observer Cooperative Behavior

We begin with the assumption that a Mobile Observer has capabilities of moving its eyes, head and body system. Now consider the task of gaze control and pursuit. It is clear that the observer has several ways of accomplishing this task (moving only its eyes, moving its eyes and head, and/or moving all parts of the body system). In the simplest scenario, the eye, head and body are aligned. Although one has a redundant control system, one can use the constraint of alignment to get the optimal solution. However, the case is not so simple if the target of pursuit is in a different orientation than the body because of some obstacle avoidance need. While the gaze control in the first case is rather simple, in the second case the control of the eye and the body must be decoupled, though the eye position changes as the body moves. Hence, they have to cooperate and excite or inhibit each other depending upon the task.

We have developed some simple behaviors for obstacle avoidance and tracking, and modeled them as a Discrete Event Dynamic System. An example is shown in Figures 14 and 15. The more complex behavior of obstacle avoidance while tracking, i.e., combining



Task: move the object from one location to another (including position and orientation).

Coordination requirement: (1) stably grasp the object all the time; (2) avoid unnecessary cancellation in effort.

Rolling constraint: the two contact forces F_1 and F_2 must be kept within the friction cones.

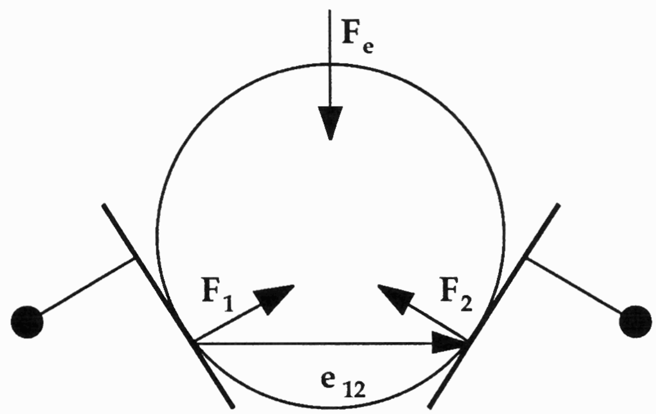
Figure 8: Two-Arm Manipulation (2-D Case).

the simple behaviors, is shown schematically in Figure 16.

2.6 Agent-Agent Cooperation

There are at least two different cases: a) when two agents are physically connected by holding one object (this case was discussed at the manipulatory level); and b) when two agents are physically disconnected but have a common task and cooperate. In both cases one of the most difficult issues is what do the agents communicate, and how much independence must they give up for the sake of cooperation. With physically connected agents, the communication proceeds through the physical media, where each agent senses the forces. For simple movements, as shown in the above example, this communication is sufficient. The more intriguing case is when the two agents are physically disconnected.

At this point we have more questions than answers. Consider, for example, two mobile observers looking approximately at the same target. How do they know that it is the same



Planning Objectives:

- ☐ Counterbalance F_e = gravity force + inertia force + disturbance force
- ☐ Maintain the desired critical interaction force $F_I^d(t)$
- ☐ Keep F_1 and F_2 at (or close to) the center of friction cones
- ☐ Satisfy the force ellipsoid (joint torque limit) constraints

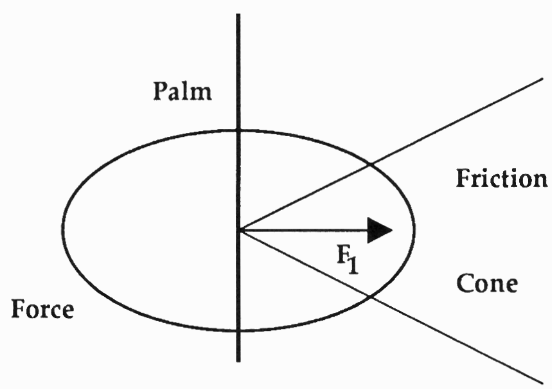
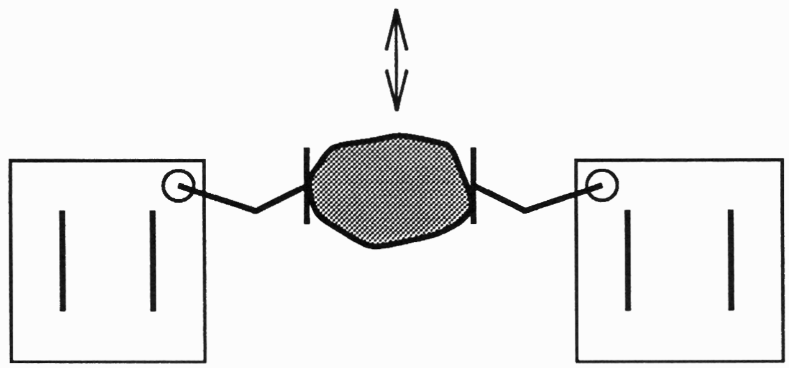


Figure 9: Motion Planning for Rolling

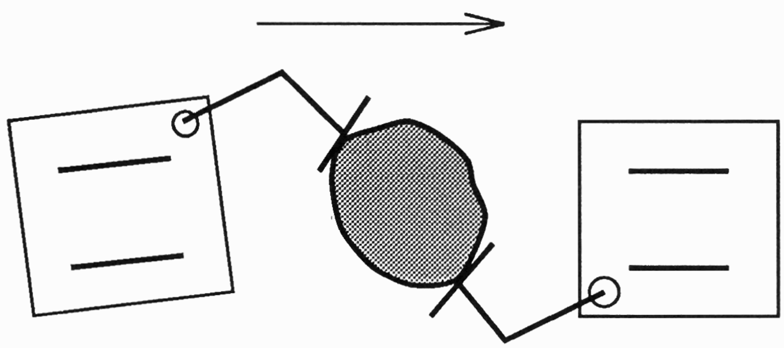


☐ Coordination between two platforms is required.

☐ Manipulation is less coupled with locomotion than in the serial following scenario.

☐ Easier to switch Master/Slave relation between the two agents.

Figure 10: Coordination of Two Mobile Manipulators — Parallel Marching

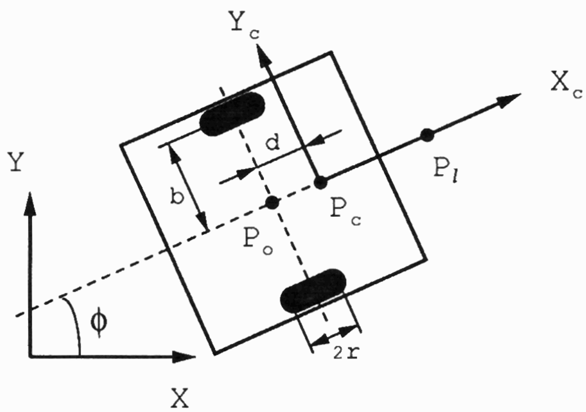


☐ Strong coupling between manipulation and locomotion.

☐ No explicit coordination is needed between the two platforms.

☐ The coordination of two agents is achieved as a consequence of the self-configuration of the slave agent.

Figure 11: Coordination of Two Mobile Manipulators — Serial Following



Lateral velocity constraint:

$$\dot{y}_c \cos\phi - \dot{x}_c \sin\phi - d\dot{\phi} = 0$$

Rolling constraints for the driving wheels:

$$\dot{x}_c \cos\phi + \dot{y}_c \sin\phi + b\dot{\phi} = r\dot{\theta}_r$$
$$\dot{x}_c \cos\phi + \dot{y}_c \sin\phi - b\dot{\phi} = r\dot{\theta}_l$$

Figure 12: Wheeled Mobile Platform

target? Or consider two mobile agents that must get through a narrow passage. In a cooperative fashion they must decide who goes first and who goes second. The decision making process must include the rules of the road. If the rules do not arbitrate sufficiently, then the cost function enters, which depends upon the cost measured in the time and energy expended getting through, and the cost of failure (how much time it will take to back up). This cost function is derived empirically. If everything fails, the agents ask the human agent for arbitration.

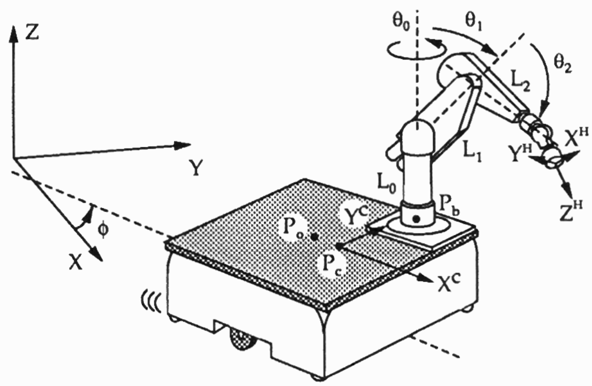
This leads us to the Advice Giving and Advice Taking Architecture, a small team architecture of 5-6 agents. The principles are as follows:

a) There is no boss!

b) Different agents, including the human agent, have different, superior capabilities. That is, different agents have views of the world with different granularity/resolution and therefore more or less competence capabilities.

c) Agents communicate on the basis of need, given the subtask during an interval of time.

d) The human agent has the world of activity on her screen, updated with sensory infor-



Nonlinear state feedback controller is developed for the mobile platform.

The motion of the platform is controlled such that the manipulability measure is maximized for the manipulator. The manipulability measure w is given by

$$w = \sqrt{\det J\ J^T}$$

where J and J^T are the Jacobian matrix for the manipulator and its transpose, respectively.

Figure 13: Coordinating Locomotion and Manipulation of a Mobile Manipulator

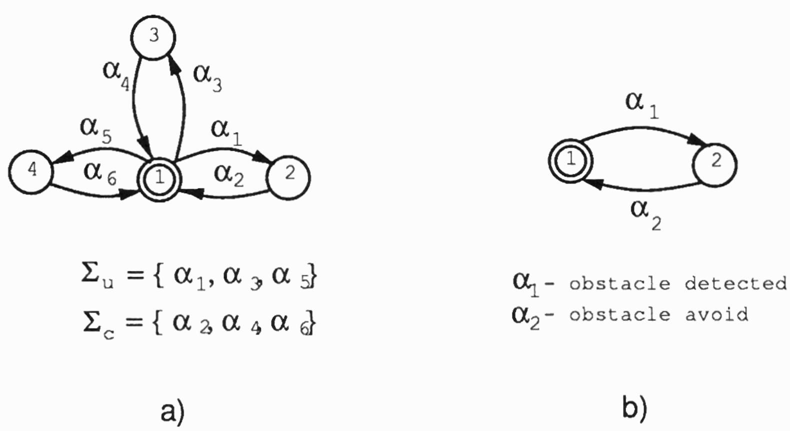


Figure 14: Obstacle Avoidance

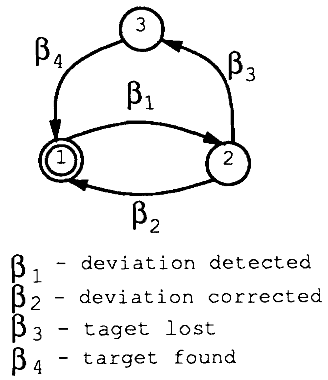


Figure 15: Tracking

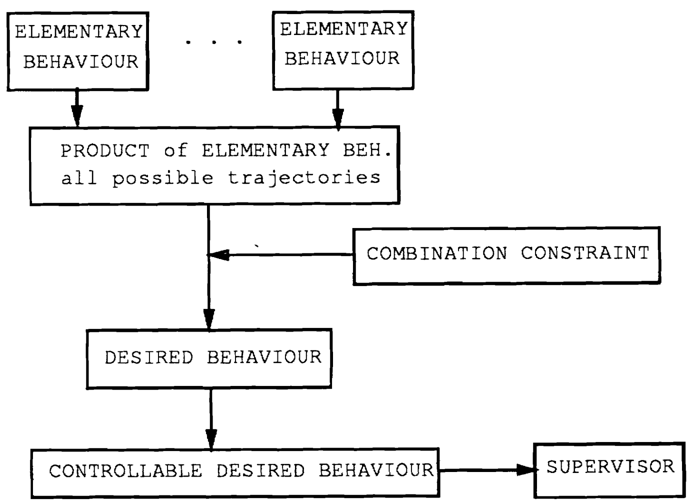


Figure 16: Complex Behavior

mation as the task is being carried out. She can switch between the global view with coarse resolution and the local view of an individual agent, depending on the demands of her decision making.

2.7 Conclusion

We have tried to motivate the case for distributed cooperative agents. During our studies of cooperation as a process, we have found that it occurs on many different levels: sensory, manipulatory (when there is physical contact) and finally when there is no physical contact. In the last case, there must be a *common task contact.* It is the common task, the shared world and knowledge that enable cooperation. Cooperation also allows for an organization without a *dictator*! Hence, our architecture of Advice Giving/Taking which subsumes intelligent communication and a voluntary sacrifice of some independence for the common good.

3 Current Research

3.1 Decision-Making Research

3.1.1 Some Applications of Statistical Decision Theory to Noiseless Data Compression and Probability Estimation

Kevin Atteson and Max Mintz

Given a sequence of data generated from a known probability model, it is possible to encode the data to achieve optimal data compression. However, in practice, the probability model is often not known or the data may not be generated by a "true" probability model at all. In such cases, it is common to estimate the probability model from the data. While many methods exist for this estimation, in many cases, it is not known which methods are optimal. In this research, we apply some techniques from statistical decision theory to the problem of data compression and derive optimal rules of estimation. In particular, we derive Bayes and minimax rules for this problem. Bayes rules are optimal rules when there is prior information in the form of a prior distribution on the parameters to be estimated. Minimax rules are "conservative" optimal rules when there is no such prior information.

We derive a general form for Bayes rules for this problem. We introduce a class of probability models in which the probabilities change occasionally. This model class is intended to provide a more accurate account of transmission lines where data with different probability models are sent over time and may also apply to other situations in which the probability models change. Minimax rules prove much more challenging. Unlike the Bayes rules, the minimax rules are dependent upon the number of data samples. We derive minimax rules for asymptotically large number of data samples for a class of Markov chains. These optimal rules appear to be computationally infeasible but are nonetheless useful for the evaluation of other rules.

Some authors, such as Rissanen, claim that many statistical estimation problems should be framed as data compression problems. The basic idea is that the principle purpose of statistical estimation is in finding a concise description of the data, i.e., compressing the data. If one accepts this tenet, then the results described briefly above have widespread application to the problem of probability estimation.

3.1.2 Theoretical Foundations for Multisensor Data Fusion: Fixed Size Confidence Intervals for Non-MLR Problems

Gerda Kamberova and Max Mintz

During 1992 we continued our research on robust sensor fusion. We examine sensor fusion problems for location data models, $Z = \theta + V$, using statistical decision theory. We

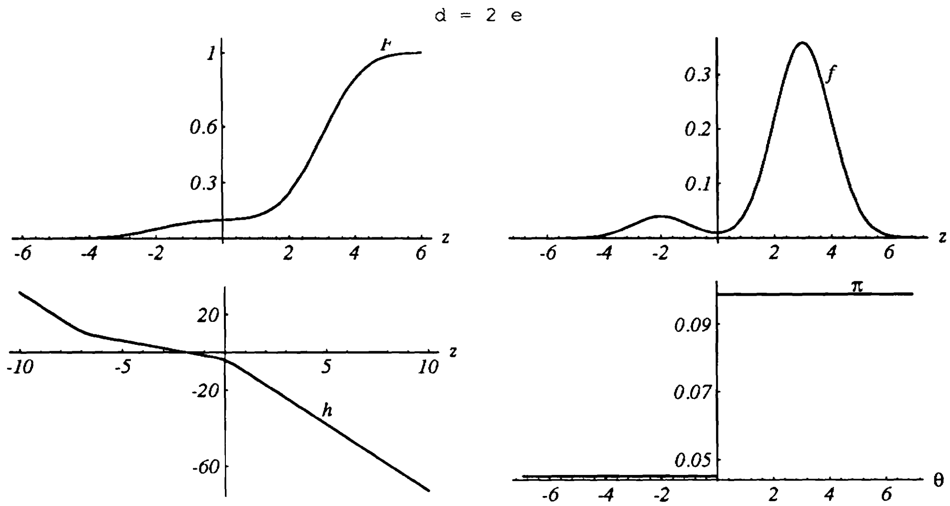


Figure 17: Example – a Gaussian mixture $F[z] \;=\; 0.1\Phi[z+2]+0.9\Phi[z-3]$.

obtained optimal and near-optimal fixed size confidence intervals for the parameter, θ, of the sampling distribution, $F(z-\theta)$. These confidence intervals are based on related minimax rules (minimax with respect to zero-one loss with error tolerance e). Prior information about the parameter is captured in terms of a known compact interval, $\theta \in [-d\,,\,d]$. Our previous results dealt with distributions with monotone likelihood ratio (MLR). During 1992 we obtained results for non-MLR distributions. These distributions are important in modeling real-world sensors.

Monotone minimax rules

For a large family of non-MLR absolutely continuous distributions we derive the explicit structure of the optimal monotone-minimax rules and sufficient conditions under which these monotone rules are globally minimax Bayes rules. This family contains very general shift and scale mixtures of Gaussian distributions (including asymmetric, bimodal distributions).

We illustrate the theory with a simple example presented at Figure 17. Let Φ be the standard Gaussian distribution, $e = 3.477318$, F be a mixture of two Gaussian distributions, $F[z] \;=\; 0.1\Phi[z+2]+0.9\Phi[z-3]$, and f be the density of F. Denote $h(z) \;=\; \log(\,f(z+2e)/f(z)\,)$. The monotonicity of h is sufficient condition for the monotonicity of the global minimax Bayes rule δ^e_m. This rule is monotone increasing piecewise-linear specified by a parameter $a_0 = 1.22397$. The increasing segments of δ^e_m have slope one. The prior density π for δ^e_m is piecewise-constant. The MLE estimator for θ has the same structure as δ^e_m. It is specified by a parameter $a_{mle} = 3$. The maximal risk of the MLE estimator is 0.093836. The maximal risk of δ^e_m is 0.04. Both rules are depicted at Figure 18.

Nonmonotone near-minimax rules

Next, we consider non-MLR distributions for which the minimax rules are not monotone. For a given error-tolerance, e, and a symmetric absolutely continuous distribution, F, we

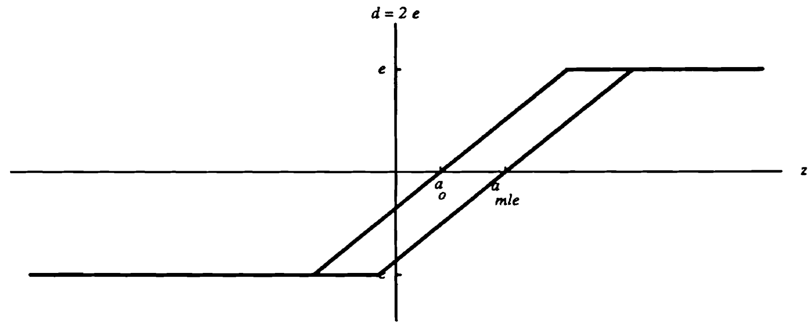


Figure 18: The minimax rule δ^e_m and the MLE estimator.

define a distribution-dependent family of functions

$$Q_{F,e} = \{\, Q^1_c(x) = F[\,2e - F^{-1}[\,c - x\,]\,] - F[\,2e - F^{-1}[\,1 - x\,]\,] \,:\, 0 < c < \frac{1}{2}\,\}.$$

When Q^1_c are monotone nonincreasing functions, the minimax rules are monotone. Nonmonotonicity and convexity of Q^1_c are sufficient for nonmonotonicity of the minimax rules. Examples of these sort of distributions are the Cauchy distribution, and Gaussian distributions with heavy-tailed contamination and mixtures of these. Figure 19 depicts densities and corresponding functions Q^1_c for a symmetric location mixture of Gaussian distributions and symmetric scale mixtures of Gaussian and Cauchy distributions. Although the location mixture of the two Gaussian distributions is not MLR, the corresponding function Q^1_c is monotone. Thus, the monotone almost equalizer rule is minimax and admissible. For the mixtures of Gaussian and Cauchy distributions the corresponding function Q^1_c is nonmonotone.

For CDFs, F,characterized by nonmonotone Q^1_c, we do not compute global minimax rules. But, utilizing $Q_{F,e}$, if $Q^1_c$are convex, we obtain: (i) a class of nonmonotone almost equalizer rules which achieve near-minimax risk; in particular, in the case of the Cauchy sampling distribution we show, by example, that the risk is within 0.3% of optimal; (ii) a tight lower bound on the global minimax risk; (iii) give interpretation of the best monotone rule and its risk in terms of that family; and (iv) solve the minimax problem for a discrete parameter space, thus we treat uniformly the discrete and the continuous parameter space problems.

3.1.3 Minimax Estimation Under Multilevel Loss

Robert Kennedy and Max Mintz

We consider minimax estimation of a restricted location parameter under symmetric multilevel bowl-shaped loss for a symmetric sampling distribution with monotone likelihood ratio. Multilevel bowl-shaped loss functions are obtained by a convex combination of n zero-one loss functions with given width parameters. Sufficient conditions for minimax

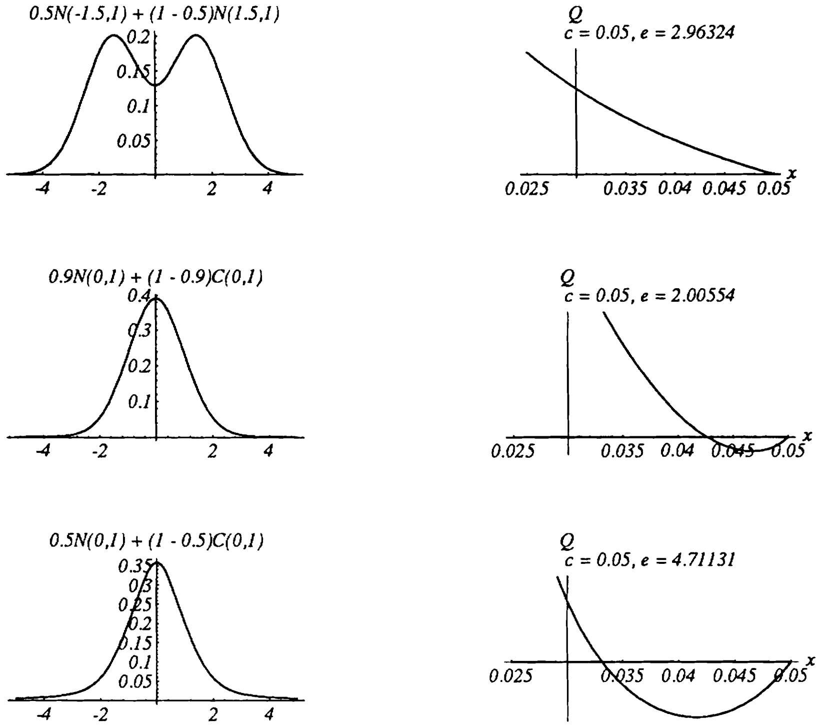


Figure 19: Examples of non-MLR densities and corresponding functions Q_c^1.

Bayes rules are obtained. These conditions are easy to check numerically. The minimax rules possess the following structure: the rules are continuous (or piecewise-continuous), piecewise-linear functions with alternating segments of zero and unit slope. These rules are simple to compute numerically. Further, we show: (i) how to approximate arbitrary symmetric bowl-shaped loss functions using multilevel approximants; and (ii) how to obtain accurate approximations to the minimax rules for decision problems with symmetric bowl-shaped loss functions and restricted parameter spaces. An outcome of this approximation study is the result that the minimum Fisher information prior ($\cos^2$) defines a bounding envelope for the least favorable prior distributions when the scale parameter of the sampling distribution tends to zero. These results extend the work: (i) on zero-one loss by Zeytinoglu and Mintz [Ann. Statist. 12(1984):945-957], and [Ann. Statist. 16(1988):1241-1253], and (ii) on the role of the minimum Fisher information prior by Bickel [Ann. Statist. 9(1981):1301-1309].

3.1.4 Active Sensor Fusion for Mobile Robot Exploration and Navigation

Robert Mandelbaum and Max Mintz

During 1992, work began on the development of a platform on which experiments in sensor fusion for mobile robot exploration and navigation could be performed. All sensors were placed on a LabMate mobile platform, and the development involved

- Construction and mounting of a suite of UltraSound and InfraRed sensors,
- Construction of a stereo head mount, to allow implementation of an Inverse Perspective Projection algorithm,
- Construction of a light source and camera mount for a patterned light sensor without the use of hazardous laser light,
- Development of software for control of the mobile platform, interfacing to the Ultrasound/IR hardware, as well as rudimentary (though effective) signal processing of the patterned light data, and
- Development of a software framework to facilitate and control the confluence and subsequent integration of the heterogeneous sensor data. Sensor modalities can hence be developed in a modular fashion, while the framework enables cooperation on a system level.

  This framework currently allows any combination of sensor modalities to be employed for any particular experiment, simultaneously taking care of all inter-module communication details as well as the low-level communication with, and control of, the mobile platform itself. Set-up time for experiments is thus reduced dramatically.

  Recent examples of experiments which have benefitted from this architecture include attempts to fuse ultrasound and patterned light data to detect and describe objects in the robot's vicinity as well as an investigation into obstacle-avoidance using Inverse Perspective Projection.

The development of these hardware and software frameworks now allows experiments to progress from the conceptual stage to physical implementation within a few days.

We are currently investigating various paradigms for active sensor fusion and feature integration for the purposes of exploration of a static environment, and subsequent navigation therein. One such paradigm involves use of the accoustic sensors for primary detection and range localization of an object. The Inverse Perspective Projection algorithm can be employed for initial azimuthal localization of the object. Thereafter, an active sensing strategy is invoked, causing the mobile robot to follow a trajectory which brings the object into view of the patterned light sensor. In this way, relatively accurate information can be accumulated regarding object position, extent and orientation. The paradigm is modular sensor-wise, while all sensors cooperate.

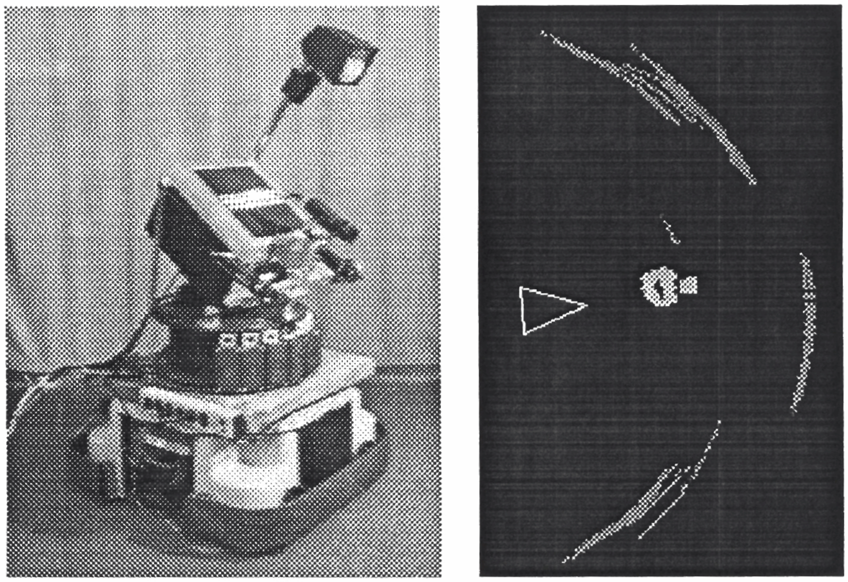


Figure 20: a) The experimental platform with its suite of sensors: Ultrasound, InfraRed, Patterned Light and Stereo Cameras. b) Sample data from UltraSound and Light Striper. This represents a plan view of a workspace. The triangle represents the mobile platform, the various arcs represent potential locations of Ultrasound reflectors, and the doughnut-looking shape is the Patterned Light sensor's rendition of a coil of cable placed in the platform's path.

We investigate the class of objects which are distinguishable using these sensors and this strategy. In this way, it becomes apparent what additional information would enhance the discriminatory power of the system, and, hence, which additional sensors would compliment the current suite.

We further investigate strategies to reduce uncertainty arising from noisy feature detection. This work builds on a strong theoretical foundation laid by former Graspees McKendall, Kamberova and Kennedy.

We explore methods to compensate for accumulating dead-reckoning errors. Proposed strategies range from elementary beacon-finding, through the so-called "bread-crumb model", to sophisticated landmark detection. New approaches to knowledge representation and manipulation are fundamental to this research.

As the future direction of research, we hope to extend the methods and paradigms developed for the fusion and integration of sensory data to the area of cooperation and information-sharing among multiple agents. Agents are clustered into task-forces and must cooperate to achieve a common goal.

Major research issues include

- efficient selection of task-forces from among agents of heterogeneous sensory and manipulatory capabilities (analogous to selection of which sensor suite to use for a particular task),
- intelligent deployment of agents to exploit individuals' particular strengths and aptitudes (analogous to selection of the optimal sensor for a specific sensing subtask),
- information dissemination: who should be told what? (analogous to the determination of which sensors would benefit from knowledge of other sensors' feature extractions), and
- communication and cooperation among agents (analogous to sensor fusion and integration, which make the whole greater than the sum of the constituent parts).

3.2 Robotics Research

3.2.1 Human Operator Interface to a Multi-Agent Robotic System

Julie Adams and Richard Paul

We purpose to use a human operator interface with generalized teleprogramming techniques to create a semi-autonomous system in which the mobile agent can be corrected without the need for physical human intervention. The operator will be located at a remote site and have no direct contact with the purposed environment. The operator will have access to all sensor data from each mobile agent, an overhead image of a portion of the environment, as well as images and processed data from the observer agents positioned throughout the environment. The human operator will use this information to build and update a graphical three dimensional world model, monitor the mobile agents progress, and interact with the agents.

Currently, we are working with a graphical three dimensional world model of the GRASP Lab. This model contains permanent and semi-permanent objects such as tables, walls, doorways and computers. We add objects to the world model using information from the overhead image of the environment. This image is a limited view, covering only a 15 by 11 foot area.

We have written a program to convert objects from this image into three dimensional objects for the world model, with the height being a static value for all objects. The program calculates the objects translation, rotation, scale, and scale orientation as well as translating all coordinate information from the overhead camera coordinate system to the world model coordinate system. This information is then added to the world model, Figure 1. In the future, we plan to use information from the observer agents to determine height values of objects in the environment.

At this time, we are working on creating a path for a mobile agent through the environment which will be displayed on the world model and verified before the agent begins to move along the path. The human operator will specify a start point, an end point, a heading and a set of way points to the system for path planning. A plan will be returned which will be displayed on the world model. The human operator will then have the opportunity to either interactively change the plan or respecify the set of way points and allow the planner to replan the path.

Finally, we are studying potential display options for the sensory data received from the mobile agents. Currently, this data includes information from infrared and ultrasound sensors, light stripping, odometry and optical flow fields. It is important to create useful displays which portray the information in the most meaningful manner to the human operator and are easily manipulable.

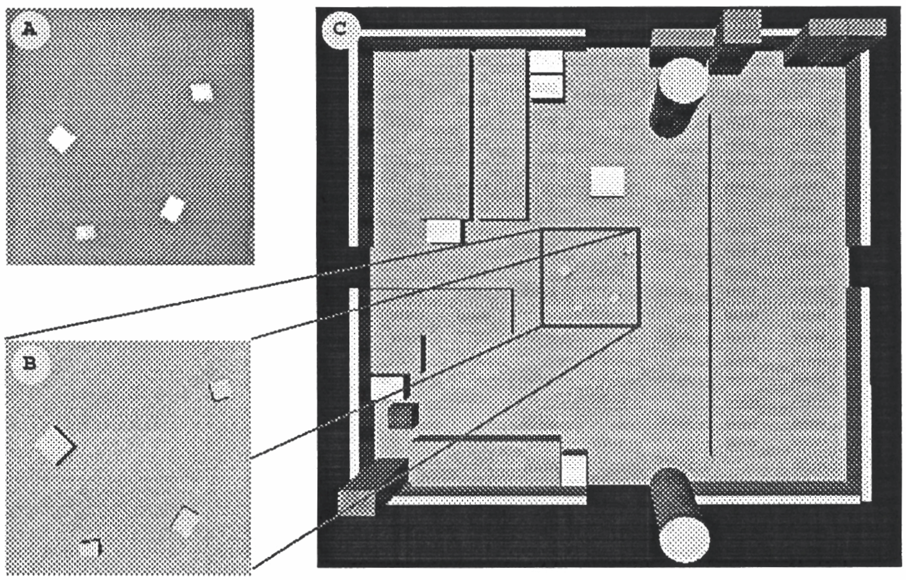


Figure 21: An example human-user interface
A: The raw image from the overhead camera.
B: The magnified potion of the world model which includes the objects as viewed from the overhead camera.
C: The complete graphical three dimensional world model.

3.2.2 Walking Chairs for the Disabled

Venkat Krovi , Parris Wellman, Richard Oh and Vijay Kumar

The mobility of the disabled, to date, has been mostly restricted to wheelchairs for use only on flat and firm terrain. The objective of this project is to demonstrate the feasibility of the "Walking Wheelchair" concept and its ability to provide enhanced mobility over conventional wheelchairs in a variety of terrains. The choice of the structure of the wheelchair was guided by several factors. Legged systems offer the advantages of omnidirectional motion and superior mobility in a variety of terrain/soil conditions. However legged locomotion systems require a complex control system for stability and motion coordination and are prone to frequent breakdowns and expensive repairs. Hence the concept of a hybrid chair, one with both legs and wheels, was more appealing as we could combine the advantages of both into one system. As it stands now, the four wheels provide the stable base as well as an energy efficient means of locomotion on even terrain. The legs provide additional traction required while traversing difficult terrains – opening up the beaches, the gardens and other vistas to the disabled. The redundant control of the various actuators gives the wheelchair added versatility and a smoother ride. The legs, when not in use for traction, can be used as manipulators and will serve as extensions of the hands of the rider. The control of the leg in free space is identical to that of an unconstrained robot manipulator. However, when the leg comes in contact with the ground it becomes a constrained dynamic system and makes the control problem more complex and nonlinear. The kinematic loop causes coupling of the position and force control. So, any control of the position and orientation of the chair will entail the control of the interaction forces at the contacts with the ground. The control of the interaction forces is important because the traction, at both the wheels and the legs, is limited. So, an algorithm which controls the position while simultaneously limiting the contact forces is necessary for the operation of the chair. As proof of concept, an experimental prototype is in the process of being built. At present, one of the legs has been built and is being tested for performance of tasks such as pulling and lifting the wheelchair. The next stage is the building of the other leg and the testing of the concepts like simultaneous position and force control. Of particular interest will be the final stages which will include gait optimization and control, foothold selection, local path planning. This will make the lower level control completely autonomous while the user commands only the direction and mode of operation using a touch pad like a rider guides his horse.

3.2.3 Whole Arm Enveloping Grasps

Stamps Howard and Vijay Kumar

The goal of this project is to develop methodology, theory, and applications for whole arm grasping and manipulation. The concept is to utilize the links (arms, if the robot is considered to be anthropomorphic) of the robot to manipulate and/or grasp an object, rather than the end effector (hand) as is normally done in robotics. There are several advantages to this approach. First, grasping an object using one's arms provides greater force since the moment arm is not as long. This is why humans usually grasp larger object in their arms rather than with their hands. A second advantage is that the location of the contact point on the arm is not position critical. Force in a given direction can be applied by any point along the length of the arm. Lastly, when a object is so large as to require two cooperating robots to manipulate it, whole arm grasping allows more contact points and thus greater stability of the grasp.

The robot used in this project is the Whole Arm Manipulator (WAM — Figure 22). It is a four degree of freedom manipulator, with three degrees of freedom at the shoulder joint and one at the elbow. The WAM is driven by a zero backlash, low-friction transmission consisting of stainless steel tendon cables, and is therefore extremely backdriveable. Because of its design, the WAM has two additional properties which make it unique: 1) Due to the tendon drive transmission, the arm has a very low inertia, and is thus capable of very quick dynamic response. Its maximum acceleration is six times that of gravity, and its maximum speed is 6 m/s (20 ft/sec). 2) Because of its very low friction, it is possible to resolve an arbitrary force acting anywhere on the outer link without the use of any force sensors. Thus the WAM is particularly well suited for force control.

Current work in whole arm manipulation involves control of the WAM in practical applications as well as theoretical work in the dynamic modeling and simulation of the

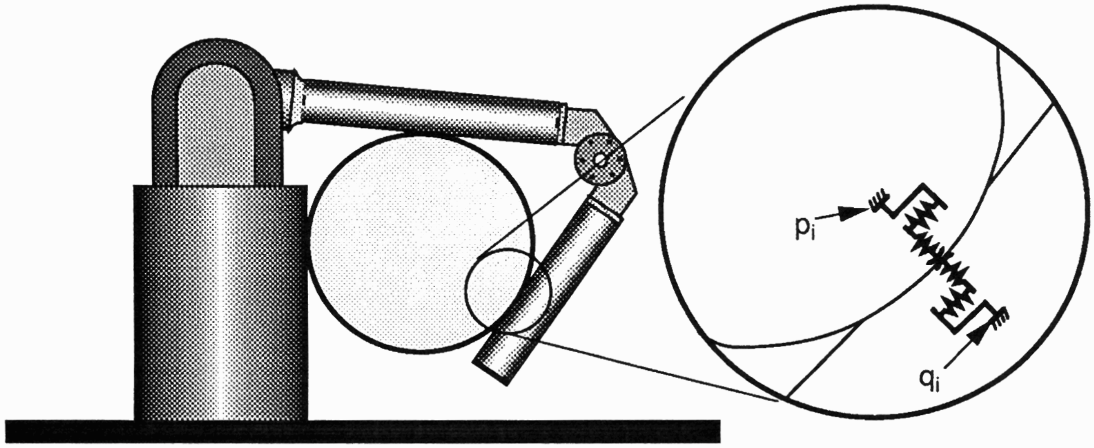


Figure 22: The Whole Arm Manipulator (WAM)

system. As an example, consider the enveloping grasp shown in the figure. It is of interest to analyze the stability and control of such grasps. In particular we are interested in finding the response of the system (including the prediction of the contact forces and slip at each contact) to different combinations of torques at the four joints. In the planar (spatial) case, there are six (nine) unknown contact forces of which only two components can be estimated (using the motor currents as measures of torque). The grasp shown in the figure is statically indeterminate, and is impossible to analyze using rigid body models.

At each contact point, we consider the point P (on the grasped object) and Q (on the contacting link) near the contact point and locate normal and tangential springs as shown. The springs have a free length that is much smaller than the characteristic dimensions of the object. We use the principle of rigid body dynamics to predict the motion of these two points. The points that come into contact are labeled p and q. The displacement of these points relative to P and Q can be determined by an algorithm developed during this project, which uniquely determines the normal and tangential forces at each contact. Thus if the history of the joint torques is known, the evolution of each contact can be predicted, and the performance of the WAM system can be analyzed.

3.2.4 Teleprogramming: Remote Site Robot Task Execution

Thomas Lindsay and Richard Paul

Since this phase of the project is completed, a brief summary of accomplishments is presented:

Instrumented compliant wrist: Two wrists are now in use in the lab, models 3 and 4. The instrumented compliant wrist device has a full six degrees of compliance, and is instrumented to measure the compliant deflection. The wrist is used for sensing and feedback for a variety of projects, including the remote site teleprogramming system described below.

Remote site teleprogramming system: The remote site for the teleprogramming system has been implemented, and testing of the complete system has validated the teleprogramming concept. The remote system accepts motion commands from an appropriate communication channel, and executes each command sequentially. The commands may be inaccurate, and the slave system, aided by an instrumented compliant wrist for sensory feedback, can compensate for errors within a predefined limit. The system can detect errors larger than this limit, and sends an appropriate error message back across the communication channel when this occurs. The most important features of the slave system are compliant hybrid control and error detection.

Remote site tool usage: The remote site system described above provided a unique environment to demonstrate the use of powered tools in conjunction with the robot system. The system provided the necessary compliant hybrid control and sensing necessary for tool usage. The powered tools introduce additional degrees of freedom to the system. However, proper use of the tool requires that the tool 'axis' be controlled and not passive. Using a proper Cartesian frame for the hybrid control, one of the robot motion axes can be aligned with the tool axis, and becomes passive. Thus for a one degree of freedom tool, the master commands the tool and five robot degrees of freedom with the same actions as controlling the robot alone: no complexity is added to the operators task. Two powered tools have been implemented: a pneumatic impact wrench and an electric winch. The performance of the system with the tools is excellent.

3.2.5 Two-arm Manipulation

Eric Paljug and Xiaoping Yun

The problem of manipulating objects which are relatively larger than the size of the manipulators is investigated. Large objects without special features such as handles can not be grasped easily by the conventional end effectors such as parallel-jaw grippers or multi-fingered hands. This work focuses on the manipulation of large objects in the plane and analyzes the contact interactions. The flat surface effectors of planar three link manipulators interact with the object. The dynamics of the object and the manipulators are included in the equations of motion that govern the planar manipulation system. The contacts between the link surface and the object can be characterized by rolling, sliding, and separation. This study focuses on rolling which is explicitly included in the dynamic model of the system. Contact separation is avoided by enforcing the unilateral constraint that each manipulator must push at the contact point. Sliding is avoided by constraining the applied force to fall within the contact friction cone. The dynamic coordination between multiple manipulators is achieved by simultaneously regulating the motion of the object and the critical contact force. Control algorithms are developed that employ nonlinear feedback to linearize and decouple the system. A motion and force planner is developed which incorporates the unilateral constraints into the system. The motion planner also specifies the rolling motion for each contact. Rolling enables the system to avoid slipping by repositioning the contact points such that forces are applied along the surface normals. The calculations of the rolling motion planner are based on the dynamics of the object, the measured external disturbance forces, and desired critical contact force. Extensions of the analysis are investigated by relaxing certain key assumptions. Simulation and experimentation are conducted to verify the efficacy of the theory and to provide insight into the issues of practical implementation.

3.2.6 Research in Inductive Learning for Robotics

Marcos Salganicoff and Ruzena Bajcsy

Learning research in the GRASP lab during the past year has focused on two major areas: the design of algorithms for learning and forgetting; and the implementation of an experimental system to pursue the experimental verification of learning algorithms for robotic tasks.

The learning algorithms are motivated by approaches used in non-parametric regression. Non-parametric regression is particularly well suited to learning tasks since many of the techniques can, in principle, handle a wide variety of distributions and classes of functions.

In particular the statistical regression techniques of Projection Pursuit and Density Estimation via k-D trees have been applied to both real-valued and categorical tasks. The Projection pursuit results are obtained for a simple grasping task and experimental system. The density estimation approach is used in the DARLING (Density Adaptive Reinforcement Learning) Algorithm. This algorithm is used for classification of different grasp types and approaches based on superellipsoid geometric data derived from a range image of the object.

An important aspect of using non-parametric regression techniques for learning tasks is that the majority of these techniques are memory-based and are therefore batch-oriented. However, one of the desired properties of useful learning algorithms is that they be on-line and adaptive to changes in the task and environment. In weight-based learning schemes and architectures such as neural-networks, the weight update rule can re-adapt weights to new functions; but in actuality, many back-propagation algorithms are run in batch mode to speed up convergence. In memory-based learning, all of the observations are kept in memory and used directly for estimates. Therefore a mechanism for *explicit forgetting* is necessary in order to delete those observations that are no longer representative of the behavior of the task. A simple mechanism, *density-adaptive* forgetting, has been implemented, which shares many of the properties of exponential-time weighted forgetting schemes that have been in wide use in control applications. However, the density adaptive forgetting mechanism uses the idea of spatial locality to selectively delete observations in regions of the parameter space only when there is subsequent evidence to supersede them. This type of forgetting has application to a wide variety of learning algorithms.

The requirements for learning in real environments demands a means for surviving action errors so that the learning process can continue. A two arm robotic system with two puma560's, one for vision and the other for manipulation has been implemented and used to gather some preliminary data along with a set of simulations to test the algorithms.

3.2.7 Control of Mechanical Systems with Rolling Constraints: Application to Robotics

Nilanjan Sarkar, Vijay Kumar and Xiaoping Yun

The nature of constraints plays an important role in determining the motion characteristics of a dynamic system. These constraints can be either holonomic or nonholonomic. While the dynamics and control issues of a dynamic system subject to only holonomic constraints are well understood, the same cannot be said about the nonholonomic case. In recent years, there has been significant interest in the area of nonholonomic dynamic systems. Examples of such systems include wheeled vehicles, satellite, legged locomotion, manipulator grasping an object and so forth. The focus of this work is on the dynamics and control problems of mechanical dynamic systems subject to both holonomic and nonholonomic constraints and its application to robotics. The type of nonholonomic constraints that are of importance here are linear in velocities, for example, *rolling* constraints.

It is well known that the motion of a mechanical system may be described by a set of, say n, generalized coordinates and differential equations of motion relating the coordinates to external forces and moments. If the system is subject to, say m, holonomic constraints, m of the generalized coordinates may be eliminated from the motion equations, although the elimination process is often cumbersome. This results in a reduced order for the motion equations . The state space representation is quite simple and the analysis and design of controllers for such a mechanical system is well understood and documented. On the other hand, if the system is subject to say k nonholonomic constraints, the number of generalized coordinates can not be reduced by k. Therefore, before well-known state space based control methods can be employed, an alternative approach is necessary to represent the motion and constraint equations in the state space.

Our objective is to present a unified approach to the control of mechanical systems subject to both holonomic and nonholonomic constraints. We first characterize the constrained systems in the state space and formulate the control problem of such systems as a standard nonlinear system control problem. Next, we show that the systems are not input-state linearizable if at least one of the constraints is nonholonomic. Since the state of the systems cannot be made asymptotically stable by smooth feedback, we pursue feedback control methods that achieve asymptotical input-output stability.

We have applied this methodology on three different dynamic systems. First, we have shown how a wheeled mobile robot can be controlled to follow a specified path with a desired velocity. Here the nonholonomic constraints arise out of the knife-edge constraint at each wheel. Next, we develop a scheme to control the contact coordinates at each contact point when multiple arms hold an object. This is done by controlling the rolling motion at each contact point. This enhances the dexterity of the system. In this context, we have developed second order contact kinematic equations for two rigid bodies in contact and used those equations to control the contact coordinates. Finally, we have shown how to maintain contact with a moving surface with desired forces, a situation which may occur in master-slave manipulation.

3.2.8 Teleprogramming: Interacting with Uncertainty

Craig Sayers, Richard Paul and Max Mintz

The teleprogramming system, developed at the GRASP lab by Paul, Funda, and Lindsay, permits teleoperative tasks to be performed in cases where the master and slave sites are connected via delayed, low-bandwidth, communications links. The problems introduced by a significant communications delay are overcome by providing the operator with a virtual reality of the remote site which provides immediate visual and kinesthetic feedback. By monitoring the operator's actions the master system is able to automatically generate a symbolic command stream for transmission to, and execution at, the remote site. Since these commands are at a relatively high level they are well suited to transmission over a low-bandwidth channel. Error detection at the slave is facilitated by the inclusion of motion and force limits within the programmed commands.

Improvements to the master station for teleoperation systems have generally focussed on improving operator performance by providing more sophisticated master arms or improved visual displays. We proposed synthetic fixturing, where the master system actively guides the operator's motions in one or more degrees of freedom, as a means of increasing precision and speed without the need for sophisticated and expensive hardware. Fixturing is accomplished by giving the manipulator a tendency to drift, in one or more degrees of freedom, toward predetermined task-dependent positions. The force is sufficiently large that an operator who wishes to make use of the fixture can just relax and let it pull their hand along and yet sufficiently small that an operator who wishes to move in a different direction can still get there – he or she just needs to push a little harder. In the teleprogramming system fixtures increase both speed and accuracy while reducing the uncertainty associated with the autonomous generation of commands (see Figure 23).

While fixtures will help the operator perform an action they won't assist the operator in deciding which action to perform. Aiding the operator in such a decision requires that they have some information regarding the likelihood of any given action being correctly executed in the uncertain world at the slave site. To this end it has been proposed that color clues be employed to provide the operator with a visual measure of uncertainty.

The final positional accuracy with which the slave robot may be controlled is a function of the uncertainty throughout the system. The use of synthetic fixturing and color clues should reduce the effects of uncertainty and improve the quality of the operator's interaction with the uncertain world.

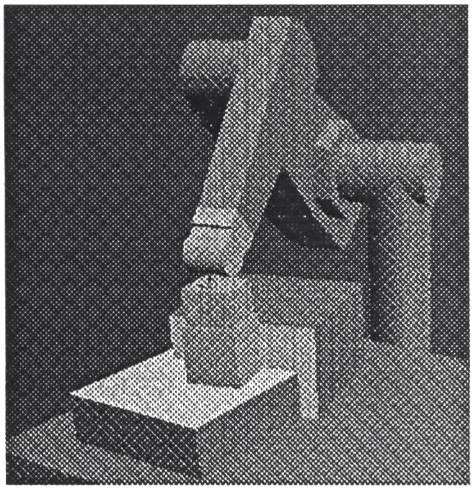


Figure 23: The virtual reality representation of the remote site - in this example a Puma 560 and a few boxes. The highlighted top of the shorter box and front of the taller box represent active synthetic fixtures which have guided the operator in moving the end-effector into face-face contacts with both planes.

3.2.9 Cooperative Research in Teleoperation

Matthew Stein and Richard Paul (University of Pennsylvania)
Paul Schenker and Antal Bejczy (Jet Propulsion Laboratory)

A challenge to the advancement of the state of the art in teleoperation is the inability of many researchers to share results. A new thrust of the telerobotics project is the establishment of a cooperative effort with the Man Machine Systems group at the Jet Propulsion Laboratory of NASA. A goal of this project will be the implementation of results obtained in the GRASP lab in the Advanced Teleoperation and Man-Machine Systems Laboratory at JPL. To demonstrate compatibility, a milestone of this project will be the teleoperation of portions of the Solar Maximum Satellite Repair - Orbital Replacement Unit (ORU) changeout experiment at JPL using a master manipulator located in the GRASP Lab. Towards this end the majority of the slave site capability of the teleprogramming system has been implemented in the Jet Propulsion Laboratory. These developments allow symbolic guarded motion commands generated in the GRASP lab using the virtual reality master station to be interpreted and executed at JPL. This capability was developed this year and a demonstration is expected this summer.

3.2.10 Kinesthetic Replay for Error Diagnosis in Time Delayed Teleoperation

Matthew Stein and Richard Paul

This development is for aiding an operator in understanding error conditions. In the Teleprogramming system, a graphic simulation of the remote robot operating in it's environment is utilized to provide real-time operator feedback. A "shadow" superimposed on the graphic simulation, has been developed . This image allows the operator to envision the actual remote manipulator motions which occurred leading up to an error condition. This display is driven by symbolic statements generated at the remote site representing motions and forces. In a situation where a remote error occurs, it is important to determine not only the current state of the robot, but also the cause of the error condition. A capability influencing the success of this determination will be the ability to provide kinesthetic information to the operator while replaying the sequence of motions leading to the error condition. To provide this capability, an operational mode has been developed in which the operator may replay a sequence of motions leading to an error condition. In this mode, control of the remote manipulator is suspended. The operator actively manipulates the master arm which is constrained to move along the trajectory corresponding to the remote trajectory. During this motion, the operator is required to apply the forces felt at the remote site in order to cause motion. In this sense, the operator will be given physically intuitive, three-dimensional information about the forces applied to the remote manipulator during the motion. This process may be repeated until the operator re-engages control of the remote manipulator. Implementation issues related to the storage, transmittal, and playback of the motion and force information, as well as user interface issues involved in the operation of the playback mode are discussed.

3.2.11 Behavior Based Control in Time Delayed Teleoperation

Matthew Stein and Richard Paul

To provide the autonomy necessary for the slave site of the teleprogramming system, a behavior based controller constructed under the principals of the Subsumption Architecture has been implemented in the GRASP laboratory. In this implementation, the behavior based controller remains simple and in the spirit of the original description by Rodney Brooks. However, included in this architecture is a level of behavior which detects conflicting behaviors at lower levels and seeks intervention from the remote operator in resolving these conflicts. At the operator station, an interface for interaction with behavior based control is defined. The operator performs the task on a graphic model of the remote environment while experiencing virtual feedback. From this interaction, commands specifying remote guarded motions, or invoking behavioral control are generated. When behavioral control is active, the operator may monitor the status of the task by following the actions of the controller using visual and kinesthetic aids. When the behavioral controller encounters a situation that it is outside of its operational domain, operator assistance is requested. Because the operator has been following the task using visual and kinesthetic replay, he may quickly diagnose the situation and correct it using normal teleprogramming. When correction is completed, the behavioral controller is reactivated and the task in continued.

The construction of a behavior based controller which utilizes operator assistance for behavioral conflict resolution has some very desirable properties including: 1) The controller may be kept compact, with a small number of states and defined behaviors, thus retaining the primary advantages of behavior based control: *simplicity* and *reliability*. 2) The geometric explosion of software for error detection and correction is avoided as the operator performs reasoning and diagnosis of unexpected conditions. 3) Higher level task representations, which do not fit well into a behavior based control architecture are avoided.

The semi-autonomous task for this experiment is a mockup of a slicing task performed during a satellite repair operation. It is necessary during the repair of a satellite to cut the securing tape along seams of panels of the Thermal Protection Blanket. The seams may only be approximately located with respect to other locations on the satellite and significant variations of the surfaces may occur. It is thus necessary for the slicing task to be performed primarily by force feedback. Despite the limitations of this task, astronauts are quite capable of performing this task easily. Direct teleoperation of this task is difficult, but it has been shown that this task can be performed with an appropriate use of visual and kinesthetic feedback. To date, this task has proven to be quite difficult to perform when communication delay inhibits the use of kinesthetic feedback. The goal of the behavior based teleprogramming system being introduced is to perform this task in the presence of significant communication delay, and to do so with a completion time much shorter than that obtainable using a more conservative strategy. For this goal to be a reality, the proposed system must be experimentally validated through a series of controlled performance experiments.

Although it has been accepted for some time that many of the plausible application of robotics involve some form of shared control between an operator and an autonomous system, little has been accomplished in defining or building the interface. Significant research issues exist investigating the interaction between an operator and a behavior based controller. This research group will continue to experiment with behavior based and other forms of semi-autonomous controllers and will seek to develop paradigms for operator interaction.

3.2.12 Design and Control of an in-Parallel Pneumatically-Actuated Manipulator

Thomas Sugar

The design and control of an in-parallel, pneumatically actuated manipulator is presented. In-parallel manipulators offer superior dynamic characteristics because of their high stiffness, low inertia, and potential for direct drive actuation. In this work, the three degree of freedom tripod manipulator is studied. The three degrees of freedom of the manipulator are exactly those that are required for force control perpendicular to a surface. These degrees of freedom are translations along the approach direction and rotations about the axes perpendicular to the approach direction.

This body of research can be grouped into three parts. First the area of force control is examined with two purposes in mind, improving pneumatic force control, and secondly understanding how force control has been traditionally implemented and the reasons for its limitations. Next, the improvement of the response of the mechanism and the implementation of different force control schemes are investigated. To improve the response of the system, shorter transmission lengths and an inner pressure feedback loop are added. Position control, force control, stiffness/compliance control, and impedance control, are all investigated. Lastly, a discussion of the possible uses of this mechanism is presented. The advantage of the parallel mechanism is the ability to regulate the force perpendicular to the surface. Thus, the mechanism can control the force perpendicular to the surface, while an arm attached to the mechanism can control the position of the end effector. This mechanism allows the hybrid position and force control problem to be decoupled. Obvious uses for applying a force perpendicular to a surface are such tasks as deburring or polishing. Another possible use could be peg insertion; a new design for peg insertion will be discussed. Lastly, this mechanism could be used as an ankle for a walking machine or a wrist for a serial robot. The mechanism can adjust for unforeseen impacts and allow the system to be used in an unstructured environment.

3.2.13 Direct Teleoperation

Desikachar Venkatesh and Richard Paul

Teleoperation is the performance of work at a distance. In teleoperation an operator exerts a force or imparts motion to a slave manipulator at a remote site through the operation on a master manipulator arm located at control site. By providing kinesthetic feedback, an operator can experience the forces and the resulting motion of the slave manipulator. In this laboratory a great deal of research is conducted in the area of teleoperation with feedback delay. If the delay between an operator's action and the feedback exceeds one third of a second it becomes impossible to perform tasks using teleoperation. With the advances in communication technology, delays can be held to less than one third of a second, so that direct teleoperation is possible between any two points on earth.

Along with kinesthetic feedback, multiple views of the remote site and audio information will aid the operator to perform the tasks with considerable dexterity. The communication operator to perform the tasks with considerable dexterity. The communication channel will have to carry, with high reliability and with precise timing, the control and feedback information of the manipulators. The communication channel will also have to carry the visual and audio information. The absolute position of the master manipulator arm will be transmitted to the slave manipulator at a rate of 500 per second. The implementation of force feedback at the master arm is yet to be carried out.

3.2.14 Velocity Control of Mobile Manipulators

Chau-Chang Wang and Vijay Kumar

In order to enlarge the effective workspace of the manipulator, it can be mounted on a mobile platform. However, the surplus degree-of-freedoms (the system is now kinematically redundant) makes it necessary to develop a strategy to allocate end-effector motion between the base and the manipulator. Because the two subsystems possess different control bandwidths, it is natural to expect the gross motion to be carried out by the mobile platform while the manipulator is a fine positioning device.

By associating with each joint, a compliance function, local solutions for the inverse rate kinematics of kinematically redundant systems can be obtained. If the second order kinematics is modeled, global integrable solutions (cyclic end-effector trajectories yield cyclic joint trajectories) can also be obtained using this framework. However, for nonholonomic systems, additional constraints must be imposed to remove the nonholonomy in the system in order to obtain such global solutions. The basic goal of allocating the end-effector motion between the manipulator and its mobile base according to user-prescribed preferences is accomplished by appropriately choosing the compliant functions. The basic method is demonstrated using computer simulations and experiments as well.

3.2.15 Coordination of Locomotion and Manipulation for a Mobile Manipulator

Yoshio Yamamoto and Xiaoping Yun

The objective of this project is to study coordination of locomotion and manipulation of a mobile manipulator. The mobile manipulator (Figure 24) considered in this project consists of a mobile platform (TRC Labmate) and a manipulator (PUMA 250 robot arm). The manipulator is installed on the top of the mobile platform. Coordination between locomotion and manipulation of a mobile manipulator is important for a number of reasons. First, combining a mobile platform and a multi-link manipulator creates redundancy. A particular point in the workspace may be reached by moving the manipulator, by moving the mobile platform, or by a combined motion of the both. Second, the dynamic response of a manipulator is, in general, faster than that of a mobile platform. Third, the motion of a typical wheeled mobile platform is constrained by nonholonomic constraints while a manipulator itself is generally unconstrained. Fourth, the mobile platform and manipulator dynamically interact with each other.

A control and planning algorithm for coordinating locomotion and manipulation of a single mobile manipulator has been developed and implemented on the mobile manipulator in the GRASP laboratory. The algorithm plans and controls the motion of the mobile platform in such a way that the manipulator is maintained in the optimal configuration in terms of manipulability measure while satisfying the nonholonomic constraints. Another problem under investigation is to control a mobile manipulator to perform the task of pushing against and following a moving surface in the environment. The solution to this problem will be essential for a mobile manipulator to interact with the environment and other mobile manipulators. In particular, the results for this study will be directly applied to coordination of multiple mobile manipulators which interact with each other in the course of task performance (*e.g.*, collectively transport a large object).

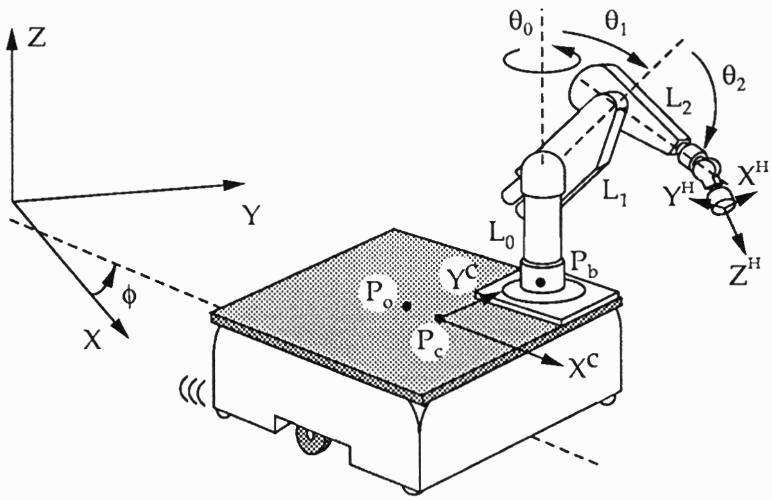


Figure 24: Schematic of the mobile manipulator.

3.2.16 Investigation of Human Two-arm Reaching Tasks with Application to Robotics

Milos Zefran, Vijay Kumar, Xiaoping Yun and Ealan Henis

When humans manipulate an object they naturally use two hands or multiple fingers to constrain the object's motion and perform the desired task. On the other hand, the control of two or more robots in similar situations is not well understood — the determination of the distribution of loads between the robots is underdetermined and the control of contact forces typically involves unilateral constraints. Numerous experiments have been performed to study the control of the motion of the limbs by the human and some of the observed principles are already used in robotics. But the bulk of this work has focused on single limb motion or even motion in a single joint. To investigate the strategies humans use when two hands interact during the manipulation task more elaborate experiments must be designed.

An experimental setup is currently being built which will allow us to study human behavior during two-arm reaching tasks. In the first phase the trajectories of the arms during reaching tasks will be studied. We will first verify some proposed models that explain the generation of the motion for a single arm and extend the models to the case when two arms are coupled. Equilibrium trajectory models in connection with impedance control (Hogan et al.) seem to be suitable candidates for this level of description. In the next phase, disturbing forces and moments will be applied during motion. The experiments can be also modified so that different levels of feedback from the arms to the brain are allowed. It is expected that the collected data will allow us to extend the existing paradigms of the human motion control to incorporate the strategies brain employs when coordinating motion of the two arms.

In the third phase we would like to apply the observed principles to the problems in multiarm robot manipulation. Friction aided grasping, control of the interaction between cooperating robot arms and problems in teleoperation are some examples of the tasks where knowing the corresponding human strategies can be of substantial benefit.

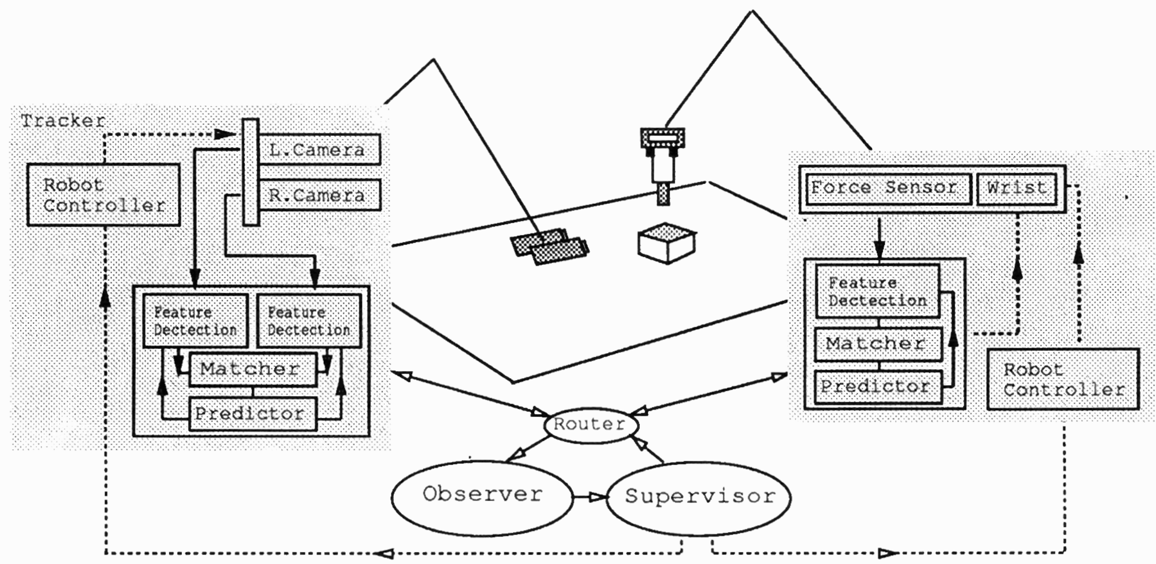


Figure 25: Vision and Force/Tactile components and their connections to both External Observer and the Supervisor.

3.3 Vision Research

3.3.1 An Active Approach to Functionality Characterization and Recognition

Luca Bogoni and Ruzena Bajcsy

Functionality in an object can be defined as its applicability toward the accomplishment of a task. We emphasize and develop an interactive and performatory approach to functionality recovery from sensor data in the context of robotic manipulatory tasks. By analyzing interaction of tool and target object and manipulation tasks as goal–oriented recognition processes we propose to identify and characterize functionalities of objects. This interaction is not only a means of verification of the hypothesized presence of functionality in objects but also a way to actively and purposively recognize the object. The representation of functionality allows us to extend the recovery process to a hierarchy of functionalities allowing complex ones to be composed from simpler ones.

A formal model, based on Discrete Event Dynamic System Theory (DEDS), is introduced to define an interactive task for recovering and describing functionality. To observe and control the recovery process we introduce the notion of piecewise observability of a task by different sensors. This allows the description of a dynamic system in which not all events nor the time of their occurrence may be predicted in advance.

A experimental system, with both vision and force sensors, for carrying out the interactive functional recognition is introduced. The vision component involves the tracking of an object by a pair of CCD cameras mounted on a Puma 560 arm. The two cameras provides us also with the ability of estimating of the distance of the object from stereo. The contact sensor, a compliant wrist with 6 degrees–of–freedom, is mounted on the end–effector of another Puma 560 arm holding the tool. The interactive behavior of the system is schematically described in Figure 25. The supervisor orchestrates the task through the feedback provided by the sensors and guarantees that the dynamic system will always be in a well defined state and that the correct sequence of operation will be performed. The observations from the individual sensors will also be provided to an external observer whose purpose will be that of evaluating the performance of the interaction.

3.3.2 Realistic Computational Models of Stereoscopic Vision

Ulf Cahn von Seelen

Many stereo algorithms cite selected evidence from neurophysiological experiments to claim biological plausibility. Yet what is really known about the neurophysiology of stereoscopic vision? How important are such ubiquitous but rarely modeled nonlinear phenomena as rectification for the behavior of stereo circuits? I am examining the existing literature with the goal of developing an accurate and detailed computational model of the early stages of stereo processing in the visual cortex. This model can then be compared with the traditional stereo approaches in computer vision and, I hope, suggest better and biologically realistic stereo algorithms.

3.3.3 Fitting 3D Deformable Models to 2D Images

Michael Chan and Dimitri Metaxas

Some success has been demonstrated using a very simple 2D superellipse model for tracking the 2D translational and rotational motion of a moving rectangular platform from 2D images. Real-time performance was achieved by formulating the tracking problem as a global optimization problem which is highly parallelizable on a SIMD architecture.

To deal with general motion of objects in a more complex world using a model-based approach, we first have to enrich our vocabulary of 3D shapes. We adopted the class of qualitative volumetric primitives called *geons* as our 3D modeling primitives. We believe that many complex human-made objects can be very well modeled by appropriate composition of part primitives from this set. It also turns out that most of these primitives can be quantitatively represented by deformable superquadric ellipsoids with only a few parameters.

While the advantage of modeling object using a small number of deformable primitive parts is clear, the problem of model recovery becomes more difficult because primitive parts of an object may occlude one another from a given 3D viewpoint. Considerable success have been made in the past to recover these volumetric primitives based on 3D range data. However, if only 2D image data is available, the task becomes more challenging.

By understanding how each 3D model primitive can be projected onto a 2D image plane, a finite enumeration of the possible *aspect graphs* of the each primitive can be obtained. Detection of these aspect graph structures in an image allow us to recognize (or to hypothesize in case of partial occlusion) the presence of the corresponding volumetric primitives [Dickinson92] quantitative model recovery.

By assuming only these qualitative constraints, a physically-based model fitting technique is developed to recover these 3D model primitives from identified aspect graph structures (possibly partially obscured or occluded) in a 2D image. 3D model are fitted to the 2D image by allowing edge data points to apply traction force to the projected 3D model. These 2D forces are mapped into forces in the corresponding natural degrees of freedom of the model through a Jacobian matrix, taking into account also the camera projection model, either perspective or orthographic. The primitive pose and model parameters are then recovered when the forces equilibrate.

Success has been demonstrated in a subset of the 3D volumetric primitives we are considering and we are applying the fitting principle to deal with the whole vocabulary of primitives. We are also extending the physically-based framework to allow us to integrate information using images from multiple viewpoints. Integration of information from a temporal sequence of images will also be another interesting subject of further research, in order to perform efficient model tracking.

3.3.4 A Neural Net Investigation of Vertices as Image Primitives in Biederman's RBC Theory

Hany Farid, Gregory Provan and Thomas Fontaine

This work investigates the importance of image vertices in Biederman's *recognition by components* (RBC) theory of object representation and recognition. In part, RBC states that object vertices are critical features for 2D object recognition: vertices contain the information necessary to segment line drawings into distinct regions. For example, consider the two line drawings below. Both are drawings of the same object (a flashlight), however, the drawing on the left is presented with a high degree of vertex occlusion, while the drawing on the right is presented with a high degree of mid-segment occlusion. Biederman showed experimentally that images similar to those on the left are unrecoverable by human subjects, while images on the right are recoverable.

This work presents a neural network model which exhibits results similar to Biederman's experimental demonstration of the importance of object vertices in human 2D object recognition. In particular, the neural network model constructed is able to correctly classify 2D objects with as much as 65% mid-segment centered contour deletion, while it is unable

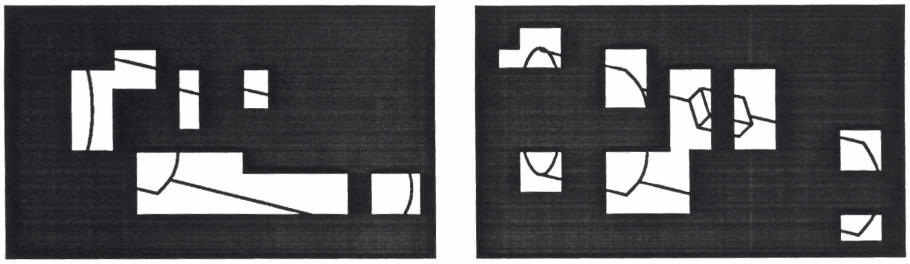
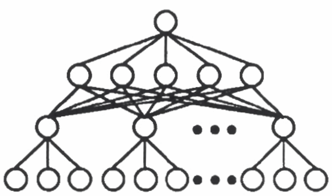


Figure 26: Line drawing of object with high degree of vertex occlusion (left) and line drawing of same object (flashlight) with a high degree of mid-segment occlusion (right). Studies by Biederman reveal that the human visual system is better able to recover objects similar to those on the right.

to classify objects with as little as 25% vertex centered contour deletion. As such, a 2D object recognition system is presented which is able to recognize simple line drawings with high degrees of noise (simulated by contour deletions). In addition, the network exhibits invariance to shifting, scaling (20%-120%) and partially to rotation (less than 15 degrees).



4-layer time-delay, recurrent neural network architecture with 30 input units, 10 units in first hidden layer, 5 units in second layer and one output unit. Training is performed using the BFGS second order learning algorithm. Binary images depicted as line drawings are presented as spatiotemporal signals.

Figure 27: Neural network architecture used for 2D object recognition experiments.

We intend to extend this work in order to achieve higher degrees of rotational invariance for 2D and 3D object recognition, and to study how neural networks can be used to "learn" invariant properties other than object vertices and geometric properties known analytically (e.g. conics, sets of lines and points, etc.).

3.3.5 Moment-Based Edge and Vertex Detection

Hany Farid and Gregory Provan

Edge detection is one of the most important processes in low-level vision; virtually every image processing system performs some sort of edge detection. Although much research has been devoted to edge detection, an optimal edge detection scheme has yet to be realized.

This work presents a new statistical approach to analyzing intensity distributions. The intensity distributions described here are taken from a *sweep* around a *target* centered at a point on the image (see Figure 28 (a)). The resulting *target intensity distributions* are classified into three categories: (b) short-tailed; (c) medium-tailed; and (d) long-tailed (see Figure 28). These three distribution types can be distinguished using a simple ratio of higher-order moments, thereby facilitating distinction of points of high curvature (which tend to have short-tailed distributions), points lying along a line (which have medium-tailed distributions), and low-frequency noise (which has a long-tailed distribution).

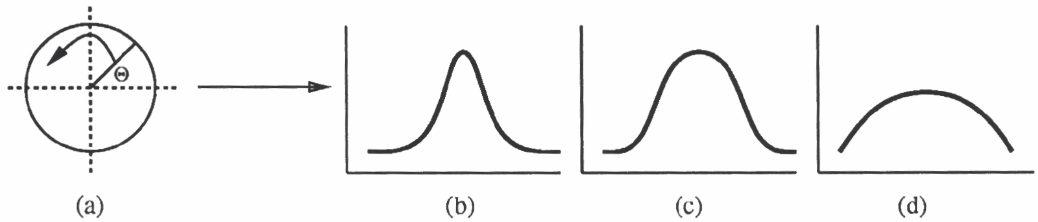


Figure 28: (a) Intensity values are averaged along a "rod" as it sweeps around a *target*; Resulting intensity distributions may be classified as (b) short-tailed, (c) medium-tailed, or (d) long-tailed.

This higher-order moment paradigm is used to design a new edge detection algorithm that has produced encouraging results. The figure below is an image of a fingerprint (left) and the results of edge detection from our moment-based algorithm (right). Results from the moment-based algorithm are comparable to that of the popular Canny gradient-based edge detection operator. However, the moment-based approach outperforms the Canny detector in areas of high curvature. This approach has also proven useful for vertex recognition, given its facility at high-curvature detection. The general applicability of this approach is currently under study.

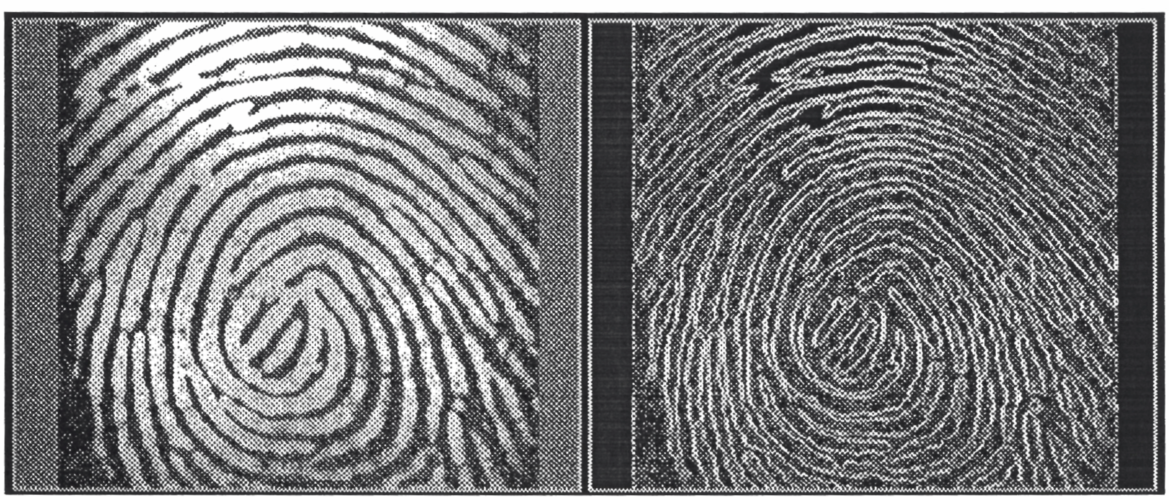


Figure 29: Fingerprint image (left) and results from moment-based edge detection (right).

3.3.6 Perception of Transparency in Moving Plaids

Hany Farid and Eero Simoncelli

When presented with two superimposed drifting sinusoidal gratings, human beings report one of two percepts: 1) the gratings appear as a coherent plaid pattern moving at a single velocity, or 2) the gratings appear to slide over each other, as if they are transparent (see below). The percept may be biased toward one of these by varying the parameters of the gratings. In 1990, Stoner, et.al. reported that when *square-wave* gratings are combined, the perception of transparency vs. coherence can be altered by modifying the luminance of the diamond intersection regions of the two striped patterns. They suggested that the rules governing this percept are the physical rules of transparent surfaces. Anecdotal evidence suggests that this is not the whole story: the percept is affected by changes in plaid angle or grating speed.

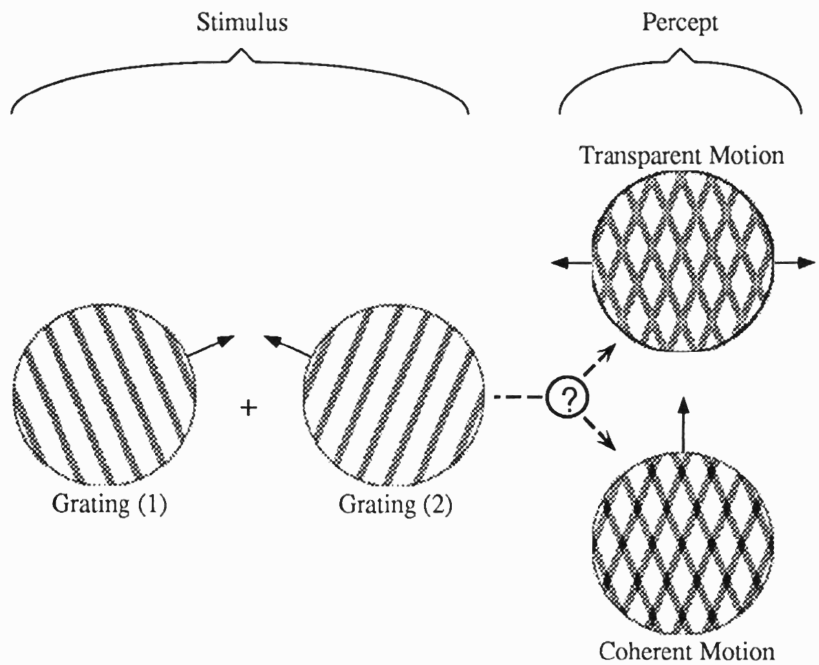


Figure 30: Stimulus consists of two superimposed square-wave gratings, human beings report seeing the resulting plaid pattern moving at a single velocity (coherent motion) or the individual gratings sliding over one another (transparent motion).

We set out to determine the dependence of the transparency percept on the other parameters of the stimulus. Our preliminary findings indicate that a second relevant parameter governing transparency perception is the unique pattern speed consistent with the stimulus (also known as the "Intersection-of-Constraints" speed). This is illustrated in figure 1. Large pattern speeds are more likely to produce a percept of transparency. Small speeds are more likely to appear coherent. Our experiments also suggest that for these symmetric square-grating stimuli, transparency perception is independent of duty-cycle, period, and orientation of the component gratings. We are in the process of gathering a more complete set of data on these phenomena, and constructing a computational model that predicts these results.

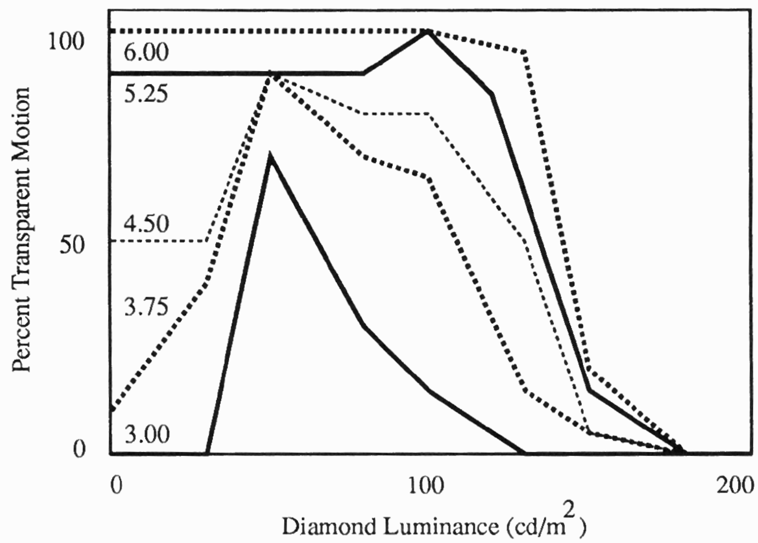


Figure 31: Perceived transparency vs. diamond luminance. Subject was asked to judge whether the pattern was transparent or coherent. Plotted are the percent "transparent" responses as a function of luminance. Each curve corresponds to a different pattern speed. At a fixed diamond luminance, the stimulus appears to be more transparent at higher speeds.

3.3.7 The Analysis of Shadows in Images by an Active Observer

Gareth Funka-Lea and Ruzena Bajcsy

Shadows occur frequently in indoor scenes and outdoors on sunny days. However, shadows in images of a scene can cause severe problems for the partitioning of the image into regions corresponding to physical objects. Consequently, prior to object recognition or vision for a mobile robot, shadows must be accounted for in an image. Despite this, relatively little work in image understanding has addressed the important problem of recognizing shadows. Shadows are difficult to identify because they cannot be infallibly recognized until a scene's geometry and lighting are known. However, there are a number of cues which together strongly suggest the identification of a shadow and which can be applied without a high computational cost.

The cues we present include color biases that apply to most shadows in a given scene, a penumbra and umbra structure, the necessity of an obstructing object, texture continuation across a shadow boundary, and the recognition that shadows remain stationary relative to the surfaces on which they are cast for fixed scene geometry. These cues address both the spectral and geometric nature of shadows. Although some cues require the recovery of information about scene geometry, we show how these cues can be applied without doing absolute depth recovery for surfaces or objects in the scene. Only image values need be examined to apply the shadow cues.

However, the reliability of the cues can be greatly improved by examining some well understood shadows in a scene. For this reason, we equip our observer with an extendable probe for casting its own shadows. Any visible shadows cast by the probe can be easily identified because they will be new to the scene. These actively obtained shadows allow the observer to experimentally determine the number, location, and rough extent of the light sources in the scene and the observer gains information about the likely spectral changes due to shadows. This information improves the effectiveness of the shadow cues.

In addition to the new methodology for recognizing shadows, our work includes a novel method for locating a light source and the surface on which a shadow is cast. It takes into account errors in imaging and image processing and, furthermore, it takes special advantage of the benefits of an active observer. In the course of identifying shadows, we also present a new modification on an image segmentation algorithm. Our modification provides a general description of color images in terms of regions that is particularly amenable to the analysis of shadows.

3.3.8 Evidence-Based Recognition of 3-D Objects using Parametric Shape Models

Ron Katriel, Gregory Provan and Lokendra Shastri

Our research is concerned with efficient recognition of three-dimensional (3-D) objects using parametric part descriptions. The parametric shape models used are superquadrics, as recovered from depth data. The primary contribution of our research lies in a principled solution to the difficult problems of object part classification and model indexing. The novelty of our approach is in the use of a formal evidential framework throughout our vision system, from surface segmentation via part classification to model indexing. The latter is amenable to the use of massive parallelism using Shastri's connectionist implementation of semantic networks.

A major concern in practical vision systems is how to retrieve the best matched models without exploring all possible object matches. Our approach is to cluster together similar model parts to create prototypical part classes which we term PROTOPARTS. Each of the superquadric parts recovered from the input is paired with the best matching protopart using precompiled class statistics. The features used by the classifier are the statistically most significant subset of parameters, computed using principal components analysis. The selected protoparts are used to index into the model database, the retrieved models are

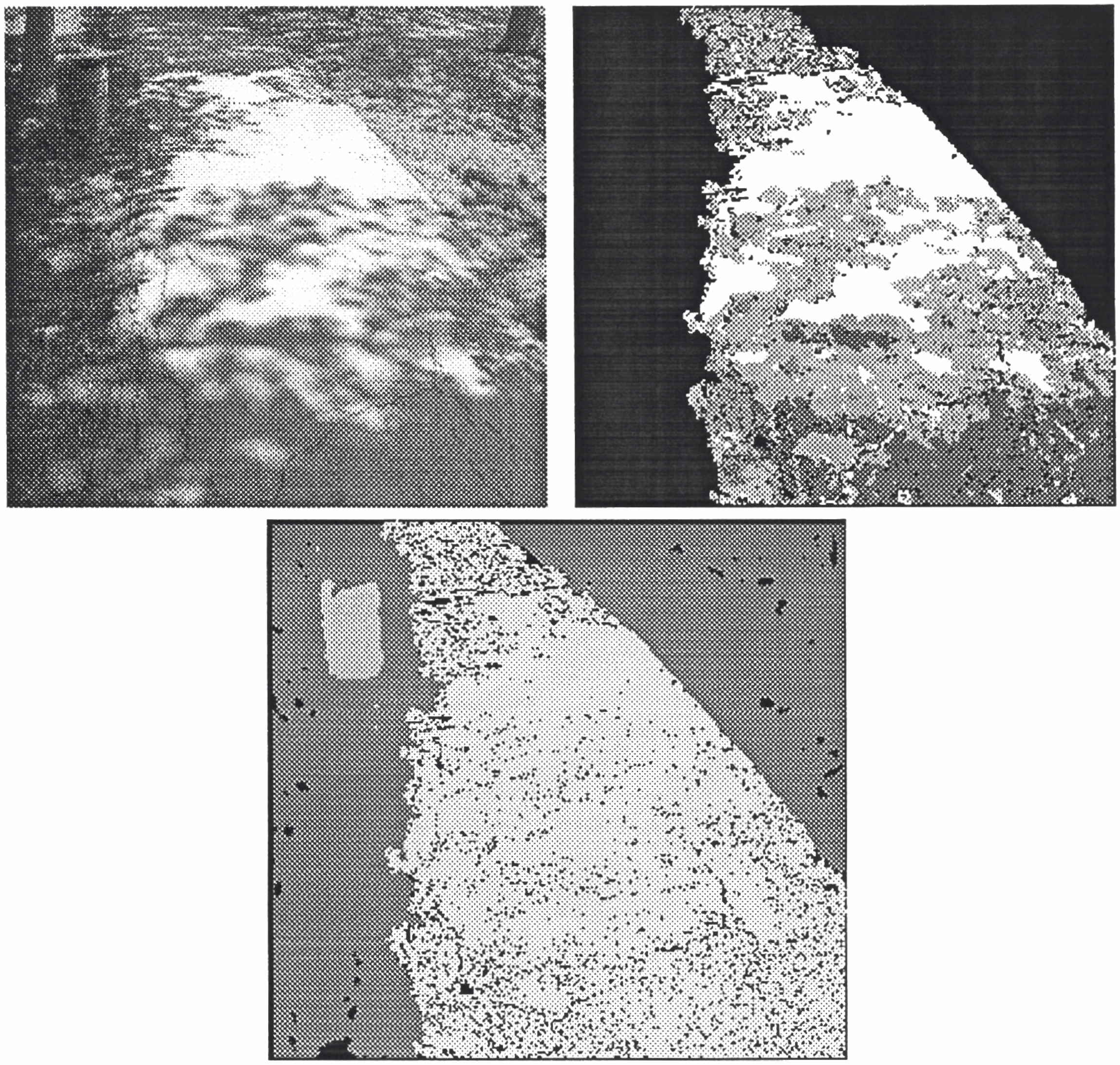


Figure 32: **Top Left:** A gray scale rendering of a color image of a road directly lit and in shadow courtesy of the Carnegie Mellon University Navlab project.
Top Right: A gray scale labeling of the umbra and penumbra of the shadows on the road as recovered by our color image segmentation for shadows. Shadow umbra is indicated by dark gray, penumbra by light gray, and the road directly lit by white.
Bottom: The full color image segmentation of the original image aimed at recovering single materials directly lit and in shadow as single image regions. The different regions are indicated by shades of gray. Black indicates that no region was found at that image position.

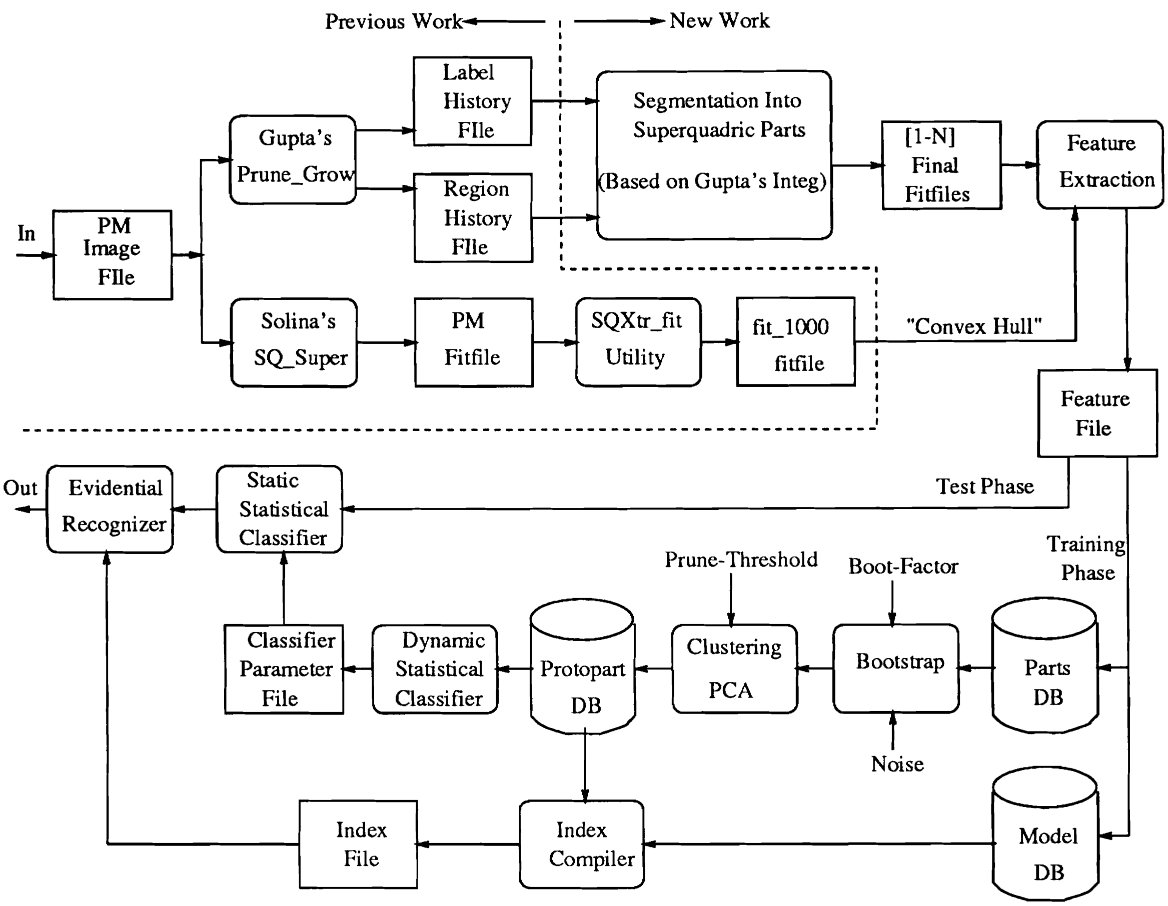


Figure 33: The Control Flow of our Evidence-based 3-D Object Recognition System

ranked by combining the evidence from the protoparts and the best matching model is output.

We have implemented a working vision system based on the principles described above. (See Figure 33.) Our work builds on Solina's technique for fitting range data from simple 3-D scenes with superquadric models and uses Gupta's scheme for segmenting range data from multi-part 3-D objects into their constituent parts in terms of surface and volumetric primitives. Our contributions includes a superquadric feature extraction module, a novel bootstrapping technique for dealing with small training databases, a statistical classifier of protoparts and the evidential model indexing algorithm.

To date, our vision system has been tested on a small database of bottles (e.g., beer, medicine, milk and wine bottles). Results indicate the promise of our approach of using protoparts as model indexing keys. At present the system assumes that the input is a range image from a single axially-symmetric object seen from a general viewpoint. We intend to extend our system to deal with self occlusion, novel viewpoints and possibly scenes with multiple objects. We are also interested in improving the user interface and implementing a top-down model verification module.

3.3.9 Robust Approach to Filtering of Scalar and Vector-valued Signals

Visa Koivunen

In our previous work we presented a class of nonlinear filters based on robust theory. We employ regression filters (RLTS) minimizing the Least Trimmed Squares (LTS) objective function proposed by Rousseeuw to attenuate noise from laser range data where each sample measures the distance from the sensor plane to the surface. The goal of the filtering task at hand is to preserve the details and the shape of the original signal while effectively attenuating both impulsive and nonimpulsive noise. Two different implementations are developed. An iterative method employs reliable first estimates to compute the filter output. A method based on random sampling tries many smaller sample clusters of the data set to find the most informative cluster. We also extend the method for filtering vector-valued signals using the same objective function. The signal components are assumed to be correlated, hence componentwise filtering does not always produce reliable results.

3.3.10 Building Procedural CAD Models using 3-D Machine Vision

Visa Koivunen and Ruzena Bajcsy

A method for building CAD model of a part from 3-D sensor data is presented. These techniques are useful as a design aid, especially for designing sculptured free-form surfaces. They can also be used for reverse engineering of industrial parts to be able to produce spare parts for objects, if no design data exists for them. Redesigning the part by hand may raise the unit price very high if only a small number of parts is needed. The obtained CAD model is a procedural description which allows us to convey structural properties, e.g. symmetry, of the part in addition to low level geometric entities. This kind of information is helpful in part analysis and process planning, for example. The model data is represented as a set of commands that generate the part geometry. The designer can then modify or improve the design, if necessary.

The data acquisition is done by using a laser range finder. Multiple representations are employed to detect primitive solids from the data, and to capture both overall structure and local deformations of the part. The CAD model building strategy and modeling primitives are selected based on the obtained volumetric and surface data descriptions and their quality. A superellipsoid model is recovered for each part to get a coarse estimate of its shape. Surface triangulation is produced when no higher level modeling primitives are appropriate. It can also be used as an initial mesh for analysis purposes. The surfaces are approximated using NURBS surfaces because of their good continuity and local control properties. The size of the control point mesh is estimated automatically from data by a local surface characterization process. The control point mesh for the surface is recovered by minimizing least squares errors. Methods for approximating surfaces of arbitrary topology are also developed. NURBS approximation is refined to meet a user given tolerance value. The obtained model data is represented both in procedural Alpha_1 modeling language and in standard product data exchange format (IGES) which makes it possible to communicate with other automation subsystems in a standardized way. Some of the obtained model primitives can be directly mapped to primitive manufacturing operations which is useful information for computer aided process planning (CAPP). Experimental results for standard geometric shapes and for sculptured free-form surfaces are presented using both real and synthetic range data. The proposed system is interfaced to MD* spray deposit manufacturing process from EDRC/CMU.

3.3.11 Discrete Event Modelling of Navigation, Gaze Control and Cooperation

Jana Košecká and Ruzena Bajcsy

In our work we investigate modeling, analysis and synthesis of visual behaviors of agents engaged in navigational tasks. We consider situations in which two agents can navigate independently or in cooperation. The tasks of agents include following a path while avoiding unexpected obstacles, following another mobile agent, observing another agent in order to report its activity, exploring the environment etc. These tasks imply the following subtasks:

1. Development of real-time vision processing capabilities that enable visual observation for either reporting or guiding navigation and/or manipulation, both in free space as well as in the presence of obstacles.
2. Development of recognition and tracking capabilities of other agents.
3. Development of a control structure for each mobile agent that couples the results of visual processing with control.

In addition to the development of vision algorithms with real-time performance, we investigate **models of visually guided behaviors** which tightly couple visual processing with control architecture.

In general, we distinguish two kinds of behaviors: one where the perception-action are tightly coupled, i.e. particular observations are directly associated with actions, (examples of these are visually guided manipulation and/or navigation, gaze control); the other where the perception-action are loosely coupled, i.e. certain observations and/or actions may be neglected by the controller or agent. In the latter case the degree of coupling depends on the degree of cooperation between the agents.

The visual capabilities of our agents at the moment comprise simple obstacle detection, target detection, and target tracking. The extraction of appropriate qualitative information from obtained sensory data allows us to develop some simple obstacle avoidance or target following strategies, or more general gaze control strategies. The behaviors are embedded in a control structure based on the theory of Discrete Event Systems (DES). The DES formalism models systems in terms of finite state automata and allows **observations** (the qualitative information extracted from sensory data) and **actions** (commands to the actuators of the vehicle or to the actuators of the observer-system) to be treated in a uniform way in terms of **events**. Events correspond here to the transitions between states and model (abrupt) discrete changes in the system's behavior (e.g. the system's behavior is different, described by different differential equations, when the gaze control is in the "gaze holding", "exploration" or "fixation" state). By separating the model of the "plant" from the "controller" we can conveniently investigate different control strategies of the plant, which can correspond to different tasks of the agent.). The DES framework is suitable for investigating control-theoretic properties of the system such as **controllability** and **observability**, which can be conveniently predicted.

The DES framework provides us with a compact description of the system at the task level, where different tasks correspond to different combinations of continuous control strategies. We must stress that the inherent continuous nature of certain control strategies is not thrown away but rather it is hidden in the states. We recall that our overall goal is to provide a theory for the cooperation of agents. For this purpose, there is an explicit need for communication. Events (observations and actions) which correspond to the qualitative changes in the environment and task execution then become natural candidates of the information to be communicated among agents.

3.3.12 Identifying Reflection Properties by Color and Multiple Views — An Active and Physics-Based Vision Approach

Sang Wook Lee and Ruzena Bajcsy

One of the goals of computer vision is the characterization of image changes in terms of the physical processes that originated them. For instance, a shadow may be distinguished from a highlight or a reflectance change, and material properties may be identified. Many efforts have been made in computer vision to achieve this goal by interpreting only image intensities using processes such as edge detection, segmentation, region growing, and groupings of local edges. However these traditional approaches have shown very limited success. Recently there have been new approaches to this problem using physical models of light reflections and image sensing, and using extra information such as color, polarization and multiple images with different lighting or viewing directions. Correct characterization of image changes by physics-based vision can facilitate many vision processes such as image segmentation and object shape/structure extraction. It also has many industrial applications such as visual inspection of surface reflectance which is directly related to the quality of surface finish and paint.

Although the physics-based approaches have shown many successful results, most physical models for surface reflections have their limitations as well as advantages, and there is no single model based on a single cue that reveals all the structure of visual information. For stable descriptions of reflection properties in general environments, therefore, it is important to understand the limitations of each model, and it is desirable to combine multiple cues in synergistic ways. The focus of our current research is to develop new methods for more general objects and scene illumination compared to those of previous methods. Our goals are to identify and locate highlights and interreflections; to identify physically different edges due to shadows, highlights, shading and reflectance changes; and to identify and discriminate different materials, such as dielectrics (e.g. wood and foliage) and metals.

We have previously developed two different algorithms for detecting highlights and inter-reflections using color and multiple views. The first algorithm is based on the dichromatic model and a image segmentation technique, and it detects and separates sharp and diffuse highlights and inter-reflections from Lambertian reflections However, it only works under the assumption that each object is made of uniformly colored dielectric material and that scene illumination is singly colored. In the second method called "spectral differencing", we exploit "Lambertian consistency" between two or more images taken from different viewing directions as a cue for detecting highlights in color images. The algorithm does not require any assumptions on object materials or scene illumination. However, it is not always efficacious for detecting diffuse highlights and inter-reflections.

We are developing a method that combines the two algorithms for detecting diffuse highlights and inter-reflections in various environments. The spectral differencing will be a preprocessing stage for detecting some highlights from dielectrics and metals. If the detected highlights are from dielectrics, we can apply local processing of color information based on the dichromatic model for finding more highlights and inter-reflections. For metals, we need to establish a model for analyzing color information around the detected highlights. We shall investigate whether material classification is necessary for this local processing. We shall also investigate the possibility of classifying materials by color.

Material classification using color and multiple views is one of our works in progress. Polarization is the only working cue for material classification, though in some limited environments. Although a basic color model for predicting material classes has been suggested previously, there have been no practical computational algorithms to realize the potential of the model for general scenes. The difficulty lies in the fact that the material type has to be determined before specular highlight detection by color, while highlights have to be detected to identify the material type. Multiple illumination colors make the problem more difficult. We are currently extending the basic model for predicting material classes using color for various object materials and illumination conditions, and investigate the use of the extended model and our highlight detection algorithms for classifying materials. Our spectral differencing algorithm does not require a priori knowledge of material types or illumination conditions for detecting specularities.

Other works in progress include the use of a light source that is located very close to an observer and casts light into an environment. The goal is to distinguish between the edges due to highlights, shadows, shading on object shape change and reflectance change.

Environmental light (indoor and outdoor scene illumination) is an extra source that provides this information. The active light generates extra shadows and highlights, and their edge locations are in general inconsistent with those generated by environmental light. We look to the inconsistency of edge locations for identifying shadows and highlights, and use color for further discrimination between the shadow and highlight edges. We also use the ratio of the images under scene illumination and with active light to distinguish between the edges due to reflectance and shape changes.

3.3.13 Segmentation, Estimation and Tracking of Shape and Nonrigid Motion

Dimitri Metaxas

My research addresses the segmentation, estimation and tracking of shape and nonrigid motion. Through my physics-based framework I can construct classes of hybrid models whose underlying geometric structure allows the combination of parametric models (superquadrics, spheres, cylinders), parameterized global deformations (bends, tapers, twists, shears, etc.) and local spline free-form deformations. The construction involves modeling elasticity properties and uses finite element techniques. To deal with constrained multi-part objects such as articulated anthropomorphic bodies, I have introduced a stabilized Lagrange multiplier technique to implement hard point-to-point constraints between deformable part models. Using continuous nonlinear Kalman filtering theory, I have exploited the constrained nonrigid motion synthesis capabilities of the models in order to estimate shape and motion from incomplete, noisy observations.

We are currently working towards the extension of our physics-based framework in various directions and we already have some very promising results.

To overcome the limitation of assuming prior image segmentation necessary for the application of my shape and nonrigid motion (joint work with Sven Dickinson and Michael Chan) estimation techniques, we first use qualitative shape recovery and recognition techniques to provide strong fitting constraints to our physics-based shape estimation techniques. In particular, our technique is applicable to objects that can be described by a class of volumetric primitives called *Geons*. Secondly, we extend our previously developed technique of fitting deformable models to occluding image contours to the case of image data captured under general orthographic, perspective, and stereo projections. In particular we were able to demonstrate the use of physics-based shape estimation techniques in case of objects with surface discontinuities appearing as internal edges in an image. We are currently extending (joint work with Michael Chan) our framework to deal with more complex classes of volumetric primitives, the integration of multiple viewpoints and the development of new powerful techniques for complex motion tracking. Our resulting system will be used both for the PLAYBOT project at the Univ. of Toronto, as well as at the Grasp lab for a vision guided robot.

We have also developed a new algorithm to adaptively change the initial model discretization using adaptive finite element techniques (joint work with Eunyoung Koh). Through our algorithm the initial model grid adaptively subdivides in order to improve the error of fit of the model to the given data. Furthermore, in order to estimate the necessary model elastic parameters we are exploring the use of recursive estimation techniques. Such an improvement is necessary for the reconstruction of complex deformable objects, such as a heart, since such objects do not have uniform elastic properties.

Finally, we are also working towards the development of models which will provide more accurate reconstruction of the heart's left ventricle using MRI data and the use of new techniques for the recognition of facial expressions and body motions.

3.3.14 Distributed Representation and Analysis of Visual Motion

Eero Simoncelli

This work addresses the representation and analysis of motion in visual scenes. Visual motion is an extremely rich source of information. By observing changes in a scene over time, we can discover the three-dimensional structure of the scene, make predictions about collisions, and infer material properties of objects, such as their stiffness and transparency. Physiological and psychophysical experiments indicate that the mammalian visual system devotes considerable resources to the analysis of motion. Furthermore, the analysis of visual motion is crucial to a large number of applications in image processing and computer vision.

My approach to this problem has been to discard the traditional vector-field representation of image motion, and replace it with *distributed* representations of velocity. Distributed solutions produce robust algorithms for motion estimation, facilitate combination with other types of information (i.e., other sensory systems), and also lead to simple models of biological motion perception that account for a large body of physiological and psychophysical data. One route to a distributed representation of motion information is via an estimation-theoretic formulation of the problem. A simple Bayesian estimator with a Gaussian noise model produces a unimodal probability distribution over the space of velocities. A set of these parameterized distributions describe the motion at each point (in space and time) of an image sequence. This approach has been developed into a coarse-to-fine multi-scale estimation algorithm that operates like a recursive Kalman filter *over scale*. The resulting optical flow estimates are found to be superior to a large number of standard algorithms for recovering optical flow. I am currently working toward incorporating the probabilistic output of this model into successive stages of processing, such as the recovery of camera motion.

The distributed approach may also be extended to produce *multimodal* distributions, thus allowing the representation of multiple motions at a given image location. This is useful for estimating motion near occlusion boundaries (where the motion may be different on each side of the boundary) and in cases of shadows or transparency. Furthermore, I have used these representations to model both psychophysical and physicological data. The results indicate that these algorithms behave very much like their biological counterparts. I am currently working with researchers in biological vision to design experiments to further test these models.

3.3.15 "Shiftable" Multiscale Image Representations

Eero Simoncelli

Orthogonal wavelet transforms have recently become a popular representation for multi-scale signal and image analysis. One of the major drawbacks of these representations is their lack of translation invariance: the content of wavelet subbands is unstable under translations of the input signal. Wavelet transforms are also unstable with respect to dilations of the input signal, and in two dimensions, rotations of the input signal. I have worked with Bill Freeman, Ted Adelson, and David Heeger to formalize these problems by defining a type of translation invariance that we call "shiftability". In the spatial domain, shiftability corresponds to a lack of aliasing; thus, the conditions under which the property holds are specified by the sampling theorem. Shiftability may also be considered in the context of other domains, particularly orientation and scale. We have explored "jointly shiftable" transforms, that are simultaneously shiftable in more than one domain. We have designed and implemented two examples of jointly shiftable transforms: a one-dimensional transform that is jointly shiftable in position and scale, and a two-dimensional transform that is jointly shiftable in position and orientation. We have demonstrated the usefulness of these image representations for scale-space analysis, stereo disparity measurement, and image enhancement.

3.3.16 Range Data Acquisition and View Registration for Reverse Engineering

Jean-Marc Vezien

The Goal of the Reverse Engineering work in the GRASP lab is to obtain a comprehensive understanding of the geometry and design of a given manufactured part, though 3D sensing and computer analysis. Ideally, the output of such an analysis will be a modelization of the part usable for process planning and, eventually, manufacturing.

The focus of this work is on the input of such a system, namely, how to obtain accurate, dense and complete 3D information to provide to further analysis modules. Laser Range Finding (LRF) is the obvious choice for imaging the external surfaces of a manufactured part.

For that purpose, The GRASP lab has acquired a Perceptron Lasar LRF, based Modulated Phase-Shift technology. This type of sensor is more suited to our purpose than the more popular triangulation technology, which produces "shadows" (missing data) due to the different locations of laser emission and reception. This Lasar currently provides 12 bits

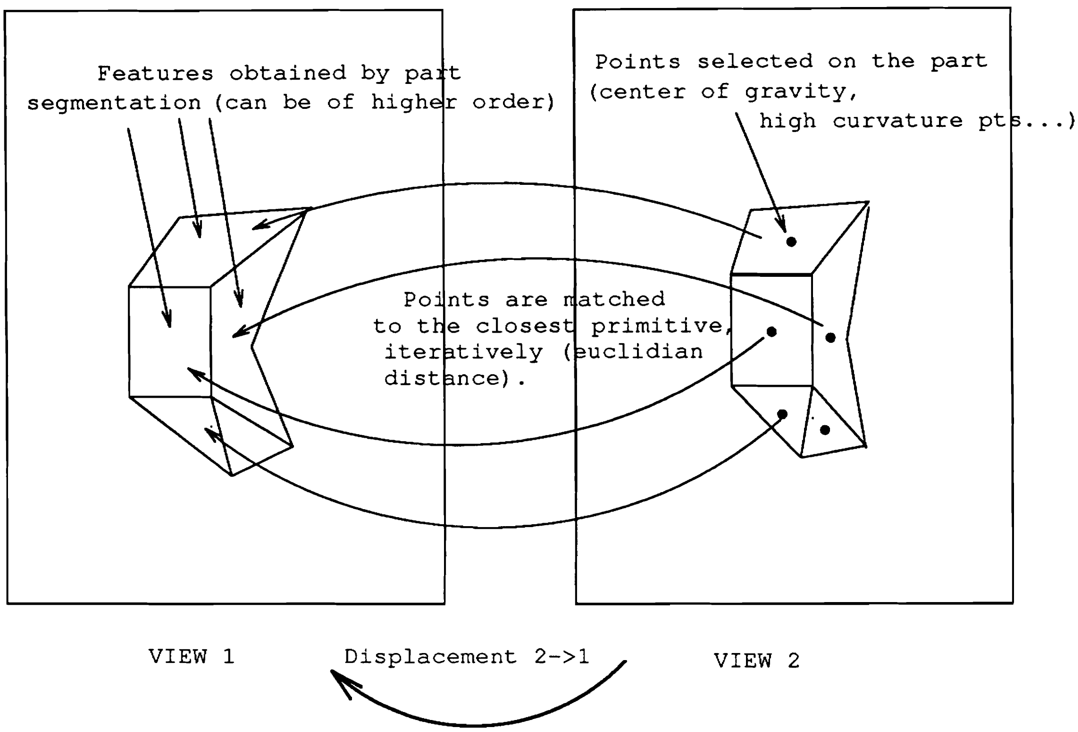


Figure 34: Principles of the view registration algorithm

images over a 2 meters range (Z-resolution: 0.5 mm). To deal with the inevitable occlusions 3-D sensing give rise to, several images from different viewpoints are needed to describe the complete shape of a given manufactured piece. It is usually impossible to directly measure precisely the rotation/translation between two given views. Hence, they must be recovered from the range images themselves. This process, also known as **view registration**, allows us to build a complete, unique 3D representation of a given part, assuming enough viewpoints were considered.

Our approach (based on Besl's ICP algorithm), consists in extracting collections of pixels according to robust, viewpoint-invariant criteria, in one view, then to compute the displacement which minimizes the distance between those features and the surface of the object as seen in another view. (see Figure 34.)

No exact matching is required between the views, thus avoiding combinatorial problems usually encountered in such matching tasks (Here, for one given displacement, a point of the surface is automatically matched with the nearest primitive. The procedure updates the displacement iteratively, so that these matches can change through time). If the object itself doesn't exhibit sufficient features, additional calibrated primitives may be added in the scene.

Currently, the algorithm is implemented using first order characteristics: a region-growing algorithm uses normal consistency to generate a planar approximation of the part.

Then the center of gravity of those planar primitives are taken as reference points to be matched against the planes extracted in another viewpoint, using the scheme explained above.

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CIS	Computer and Information Science
CSE	Computer Science and Engineering
ECE	Electrical and Computer Engineering
EE	Electrical Engineering
MEAM	Mechanical Engineering and Applied Mechanics
SSE	Systems Science and Engineering

5 Journal and Conference Publications

1. L. Bogoni and R. Bajcsy. An active approach to functionality characterization and recognition. In *AAAI Workshop on Reasoning about Function*, page , 1993.

2. M. Campos, V. Kumar, and R. Bajcsy. Kinematic identification of linkages. In *Proceedings of the 3rd International Conference on Advances in Robot Kinematics*, 1992. Ferrara, Italy, Sep. 7-9.

3. José-Antonio N. Caraza and X. Yun, Force-closed grasping with two hands, Journal of Robotic Systems, in press.

4. T. Darrell and E. Simoncelli. "Nulling" filters and the separation of transparent motions. In *Vision and Modeling Technical Report*, June, 1993.

5. H. Farid and G. Provan. Moment-based edge detection and classification. In *Work in Progress*, 1993.

6. H. Farid, G. Provan, and T. Fontaine. A neural net investigation of vertices as image primitives in biederman's rbc theory. In *15th Annual Cognitive Science Society Meeting*, Boulder, CO, June 1993.

7. G. Funka-Lea and R. Bajcsy. Active color image analysis for recognizing shadows. In *Proceedings of the International Joint Conference on Artificial Intelligence*, France, August 1993.

8. G. Funka-Lea and R. Bajcsy. Vision for vehicle guidance using two road cues. In *Proceedings of the Intelligent Vehicles '92 Symposium*, pages 126–131, Detroit, Michigan, June 1992.

9. W. Stamps Howard and V. Kumar. A minimum principle for the dynamic analysis of systems with frictional contacts. In *Proceedings of IEEE Robotics and Automation Conference*, Atlanta, GA, May 1993.

10. J.Kosecka and R.Bajcsy. Cooperation of visually guided behaviours. In *ICCV*, May 1993. (Berlin, Germany).

11. J.Kosecka and R.Bajcsy. Cooperative behaviours - discrete event systems based approach. August 1993. submitted to IJCAI 93 Workshop on Dynamically Interacting Robots.

12. J.Kosecka and R.Bajcsy. Discrete event modelling of navigation and gaze control. 1993. submitted to IJCV Special Issue on Qualitative Vision.

13. G. Kamberova and M. Mintz. Fixed size confidence intervals for non-MLR location problems (presented by M. Mintz). *IMS meeting no. 227*, 21-24 March 1993, Philadelphia, PA.

14. R. Kennedy and M. Mintz. Minimax estimation under multilevel loss. *IMS meeting no. 227*, 21-24 March 1993, Philadelphia, PA.

15. V. Koivunen and R. Bajcsy. Building procedural CAD models using 3-D machine vision In *9th International Conference on CAD/CAM, Robotics and Factories of the Future*, 1993. Newark.

16. V. Koivunen and R. Bajcsy. Geometric methods for building cad models from range data. In *SPIE Conference on Geometric Methods in Computer Vision*, 1993. San Diego, CA.

17. V. Koivunen and M. Pietikainen. Evaluating quality of surface description using robust methods. In *11th International Conference on Pattern Recognition*, 1992. The Hague, Nehterlands, pp.214-218.

18. V. Koivunen and M. Pietikainen. Experiments with combined edge and region-based range image segmentation. *Theory and Applications of Image Analysis*, 1992. World Scientific Publications, pp. 162-176.

19. V. Kumar. Characterization of workspaces of parallel manipulators. *ASME Journal of Mechanical Design*, 114(3):368–375, 1992.

20. V. Kumar. A compact inverse velocity solution for redundant robots. In *Proceedings of 1992 International Conference on Robotics and Automation*, pages 482–487, Nice, France, May 1992.

21. V. Kumar. A compact inverse velocity solution for redundant robots. *The International Journal of Robotics Research*, 12(1), February 1993.

22. V. Kumar, T.G. Sugar, and G. Pfreundschuh. A three degree of freedom in-parallel actuated manipulator. In *Proceedings of the 9th CISM-IFToMM Symposium on Theory and Practice of Manipulators*, 1992. September 1-4, Udine, Italy,.

23. S.W. Lee and R. Bajcsy. Detection of specularity using color and multiple views. *Image and Vision Computing*, 10:643–653, 1992.

24. S.W. Lee and R. Bajcsy. Detection of specularity using color and multiple views. In *Proc. of European Conference on Computer Vision*, S. Margherita Ligure, Italy, 1992.

25. J. Maver and R. Bajcsy. Occlusions as a guide for planning the next view. In *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 15, No. 5, May 1993.

26. D. Metaxas and S. Dickinson. Integration of quantitative and qualitative techniques for deformable model fitting from orthographic, perspective, and stereo projections. In *Proc. 4th International Conference on Computer Vision*, May 1993. Berlin, Germany.

27. D. Metaxas and E. Koh. Flexible multibody dynamics and adaptive finite element techniques for model synthesis and estimation. *Computer Methods in Applied Mechanics and Engineering.* in press.

28. D. Metaxas and D. Terzopoulos. Shape and nonrigid motion estimation through physics-based synthesis. In *IEEE Transactions on Pattern Analysis and Machine Intelligence*, June 1993.

29. M. Ouerfelli, W. Harwin, and V. Kumar. An inexpensive pneumatic manipulator for rehabiliation applications. In *Proceedings of 1993 International Conference on Robotics and Automation*, Atlanta, GA, May 1993.

30. M. Ouerfelli, W. Harwin, and V. Kumar. A pneumatic actuation system for a wheelchair-mounted robot arm. In *15th RESNA International Conference*, 1992. Toronto, June 6-11.

31. M. Ouerfelli and V. Kumar. Optimization of a 5-r linkage. *ASME Journal of Mechanical Design*, 1993. (in press).

32. E. Paljug, T. Sugar, V. Kumar, and X. Yun. Important considerations in force control with applications to multi-arm manipulation. In *IEEE International Conference on Robotics and Automation*, 1992. Nice, France, May 10-15, pp. 1270-1275.

33. R. Paul, T. Lindsay, and C. Sayers. Time delay insensitive teleoperation. In *Proceedings of the 1992 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 247–254, July 1992.

34. R. Paul, T. Lindsay, C. Sayers, and M. Stein. Time-delay insensitive virtual-force reflecting teleoperation. In *Artificial Intelligence, Robotics and Automation in Space*, pages 55–67, September 1992. Toulouse, France.

35. R. Paul, C. Sayers, and M. Stein. The integration of an operator with a robotic system. In *12th World Congress International Federation of Automatic Control, Sydney, Australia*, July 1993. (in preparation).

36. G. Pfreundschuh, V. Kumar, and T. Sugar. Design and control of a three degree of freedom in-parallel actuated manipulator. *Journal of Robotic Systems.* (accepted for publication).

37. A. Leonardis R. Bajcsy, and S.W. Lee. Image segmentation with detection of highlights and inter-reflections using color. *Submitted to Intern. Journal of Computer Vision*, 1993.

38. M. Salganicoff. *Learning and Forgetting for Perception-Action: A Projection-Pursuit and Density-Adaptive Approach.* PhD thesis, University of Pennsylvania, 1992. Dept. of Computer and Information Science.

39. M. Salganicoff and R. Bajcsy. Robot sensorimotor learning in continuous domains. In *Proceedings of 1992 International Conference on Robotics and Automation*, Nice, France, May 1992.

40. M. Salganicoff, R. Bajcsy, and T. Mitchell (CMU). *Learning for Coordination of Vision and Action.* Technical Report MS-CIS-92-84, GRASP LAB 337, University of Pennsylvania, November 1992. Also as published chapter of Final Report NSF/DARPA workshop on Learning Applications for Machine Vision, Hilltop, West Virginia, November, 1992.

41. M. Salganicoff. Density-adaptive learning and forgetting. In *Proceedings of the Tenth International Workshop on Machine Learning*, Morgan-Kauffman, June 1993. to appear.

42. N. Sarkar, X. Yun, and V. Kumar. Control of a single robot in a cooperative multi-agent framework. In *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems*, Yokohama, Japan, July 1993.

43. N. Sarkar, X. Yun, and V. Kumar. Control of mechanical systems with rolling contacts: applications to mobile robots. *International Journal of Robotics Research.* (accepted for publication).

44. N. Sarkar, X. Yun, and V. Kumar. Dynamic control of 3-D rolling in multi-arm manipulation. In *Proceedings of the IEEE International Conference on Robotics and Automation*, Atlanta, Georgia, May 1993.

45. N. Sarkar, X. Yun, and V. Kumar. Dynamic path following: a new control algorithm for mobile robots. *Submitted to the Proceedings of the IEEE Conference on Decision and Control*, March 1993.

46. C. Sayers, R. Paul, and M. Mintz. Interacting with uncertainty. In *Telemanipulator Technology*, SPIE Proceedings Vol.1833, November 1992. Boston, USA.

47. C. Sayers, R. Paul, and M. Mintz. Operator interaction and teleprogramming for subsea manipulation. In *Fourth IARP Workshop on Underwater Robotics, Genova, Italy*, November 1992. Also avaliable as Technical Report MS-CIS-93-15/GRASP LAB 344, C.I.S. Dept., The University of Pennsylvania.

48. E. Simoncelli (with D. Heeger.) Model of visual motion sensing. *Spatial Vision in Humans and Robots*, 1992. L. Harris and M. Jenkin, eds., Cambridge University Press.

49. E. Simoncelli and D. Heeger. A computational model for representation of image velocities. In *Investigative Opthalmology and Visual Science and Supplement (ARVO)*, Vol. 34, No. 4, 1993.

50. E. Simoncelli. *Distributed Representation and Analysis of Visual Motion.* PhD thesis, PhD thesis, MIT Department of Electrical Engineering and Computer Science, January 1993. Also available as MIT Media Laboratory Vision and Modeling Technical Report 209.

51. E. Simoncelli, W. Freeman, E. Adelson, and D. Heeger. Shiftable multi-scale transforms. In *IEEE Transactions on Information Theory*, Vol. 38, No. 2, 587–607, March, 1992.

52. M. Stein and R. Paul. Kinesthetic replay for error diagnosis in time delayed teleoperation. In *SPIE OE/Technology '92: Telemanipulator Technology*, 1992.

53. C-C. Wang, N. Sarkar, and V. Kumar. Rate kinematics of mobile manipulators. In *Proceedings of the 22nd Biennial ASME Mechanisms Conference*, pages 225–232, Scottsdale, AZ, September 1992.

54. C-C. Wang and V. Kumar. Velocity control of mobile manipulators. In *Proceedings of IEEE Robotics and Automation Conference*, Vol. 2, pages 713–718, Atlanta, GA, May 1993.

55. Y. Wang and V. Kumar. Simulation of mechanical systems with unilateral constraints. *Journal of Mechanical Design*, 1993. (in press.).

56. Y. Wang and V. Kumar. Simulation of mechanical systems with unilateral constraints. In *Proceedings of the 22nd Biennial ASME Mechanisms Conference*, 1992. ASME Pub. no. DE-Vol. 46, Eds. Kinzel et al.

57. Y. Wang, V. Kumar, and J. Abel. Dynamics of rigid bodies undergoing multiple frictional contacts. In *IEEE International Conference on Robotics and Automation*, 1992. Nice, France, May 10-15, pp. 2764-2769.

58. Y. Yamamoto and X. Yun. Control of mobile manipulators following a moving surface. In *Proceedings of 1993 International Conference on Robotics and Automation*, Vol. 3, pages 1–6, Atlanta, GA, May 1993.

59. Y. Yamamoto and X. Yun. Coordinating locomotion and manipulation of a mobile manipulator. In *Proceedings of 31st IEEE Conference on Decision and Control*, pages 2643–2648, Tucson, AZ, December 1992. Awarded the best paper prize for the Best Student Paper Competition.

60. Xiaoping Yun, "Dynamic State Feedback Control of Two Cooperative Manipulators," International Journal of Systems Science, in press.

61. Xiaoping Yun, "Object Handling Using Two Arms Without Grasping," the International Journal of Robotics Research, Vol. 12, No. 1, pp. 99-106, February 1993.

62. X. Yun, V. Kumar, N. Sarkar, and E. Paljug. Control of multiple arms with rolling constraints. In *1992 IEEE International Conferfence on Robotics and Automation*, pages 2193–2198, Nice, France, May 1992.

63. X. Yun and Y. Yamamoto. Internal dynamics of a wheeled mobile robot. In *Proceedings of 1993 International Conference on Intelligent Robots and Systems*, Yokohama, Japan, July 1993.

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