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# Dynamic Sensor-Based Control of Robots with Visual Feedback[1]

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## Abstract

Sensor-based robot control may be viewed as a hierarchical structure with multiple observers. *Actuator, feature-based, and recognition* observers provide the basis for mutli-level feedback control at the actuator, sensor, and world coordinate frame levels respectively. In this paper we address the analysis and design of feature-based control strategies to achieve consistent dynamic performance. For vision sensors, such an *image-based visual servo* control is shown to provide stable and consistent dynamic control within local regimes of the recognition observer. Simulation studies of two and three degree-of-freedom systems show the application of an adaptive control algorithm to overcome unknown and nonlinear relations in the feature to world space mapping.

## 1. Introduction

Sensor-based robot control overcomes many of the difficulties of uncertain models and unknown environments which limit the domain of application of current robots used without external sensory feedback. Both industrial arms and mobile robots require sensing capability to adapt to new tasks without explicit intervention or reprogramming While these relationships between sensing and control have long been recognized in a general sense, the analysis and implementation of specific *dynamic* control strategies has received relatively little attention. In this paper, we describe the formulation of sensory feedback models for systems which incorporate complex mappings between robot, sensor, and world coordinate frames. These models explicitly address the use of sensory features to define hierarchical control structures, and the definition of control strategies which achieve consistent dynamic performance. Specific simulation studies examine how adaptive control may be used to control a robot based on image feature reference and feedback signals.

Robot control tasks are typically defined in the *world coordinate frame* of the task environment. The environment can include the robot, objects to be manipulated by the robot, and obstacles to be avoided. The control strategy is formulated to map this world frame task definition into control subgoals in other coordinate frames. Hierarchical structures have been suggested for such a system since it facilitates modular organization and efficient decomposition of the task[1]. Figure 1-1 illustrates such a hierarchical relationship among

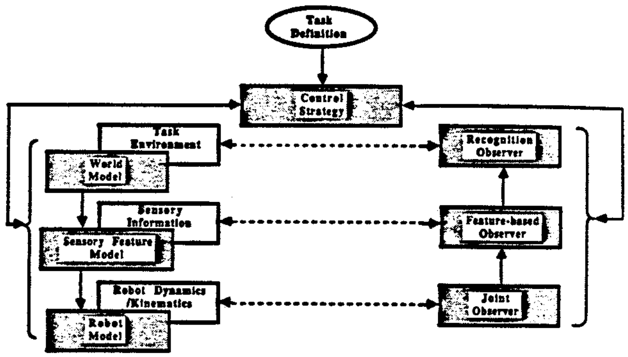


**Figure 1-1:** Hierarchical Sensor-Based Control

coordinate frames, models and corresponding observers which form the basis for the control strategy. The task definition leads to a control strategy which coordinates the mapping of commands and measurements between levels. The *world or global* model includes symbolic representations of objects and relations as well as attributes describing configurations in the world coordinate frame. The *feature or local model* includes sensor measurements and derived numerical and symbolic features which are relative to the current (local) system and sensor configuration. The *robot model* describes configurations in robot joint space.

The control strategy for the hierarchical system is based on a set of observers which relate measured signals to control commands at the various levels. At the robot model level, the *joint observer* is used by a controller to measure and control joint positions. Actuators might be coupled to rotational and prismatic joints of any arm, or wheels of a mobile vehicle. At this level, inverse kinematic models may also be used to permit reference commands be specified in the end-effector coordinate frame. At the sensor level, the *feature-based observer* derives feature values and relations from measurement data and implements task control within the local feature domain. At the world level, the *recognition observer* interprets sensory features and develops a world frame model of the current task configuration. At each level the observer output combines the task goals and constraints to generate the new command structure.

An example of a sensor-based control task is for a robot arm to acquire an unoriented object from a pallet using visual feedback control. A task level command specifies manipulation of the object; however, the robot has not been preprogrammed with knowledge of the object position. In this sense, the task environment is "unstructured". A television camera is attached

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to the robot arm and provides visual sensing capability. The image acquired by the camera must be processed by a computer vision system in order to identify the object and infer relationships between the spatial position of the object and the camera position. Such relative position information may be used to guide the robot to acquire the object from the table. The same problem arises in the navigation of a mobile robot with respect to objects in an unstructured environment using visual feedback. The images acquired by the on-board camera (or cameras) provide cues to the relative position of the robot to objects in the environment. A *local* model is used to relate image features to local robot motion, while a *global* model checks consistency of local interpretations[2,3]. Such an image processing and motion planning sequence constitutes a control loop which is coupled to both the local and global models. The dynamics of such a control structure depend critically on model representations and the maintenance of relations between robot, sensor, and world reference frames. The distribution of control among these reference frames is important to achieve good dynamic performance as well as reliable navigation.

Analysis of these hierarchical control structures which couple robot motion to unstructured environments presents a number of key issues. In particular, the dynamic performance of the system is influenced by computational delays, uncertainty, robot dynamics, and coupling in the observer itself. In this paper we examine such issues for the case of visual servo control. A recognition observer is defined for a system which infers object position and orientation from a set of derived image features. The resulting "position-based" visual servo control system incorporates the interpretation phase into its primary feedback loop. In this paper, we focus on a feature-based observer which uses image features as a basis for a hierarchical control structure. Image features which are uniquely related to spatial position are used to define task reference configurations and control robot actuators. Such an "image-based" visual servo control strategy offers advantages for reduced delay and estimation noise within a given recognition regime, as well as providing a novel "teach-by-showing" strategy for task specification.

Image-based visual servo control poses particular challenges to the observer/controller design in order to achieve consistent dynamics. The mapping between image features and the world coordinate frame may be unknown but dependent on the system configuration, as well as nonlinear and coupled. We have studied the application of an adaptive controller to achieve predictable and stable dynamic properties at this control level.

This first defines visual servo control structures, then focuses on definition and control strategies for a sensor-level feedback system with image-based observer.

## 2. Visual Servo Control

The use of computer vision to infer position and orientation of objects, or interpret general three-dimensional relationships in a scene, is in general a complex task requiring extensive computing resources. Techniques which may exploit simpler sensors, structured lighting, or minimize processing for image interpretation may offer advantages for visual servo control implementations[4,5]. In a general approach to the interpretation of a two-dimensional image for inference of three-dimensional position and orientation, a sensor, such as a TV camera, is used

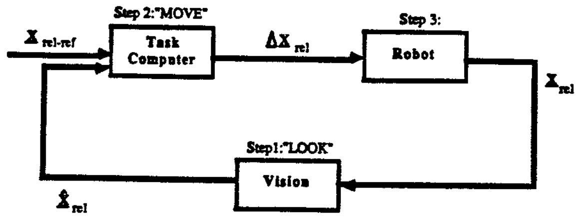


**Figure 2-1:** Static "Look and Move" Control

to acquire a two dimensional array of brightness values $\mathcal{A}$ from the three-dimensional scene. This image array may undergo various types of computer processing to enhance image properties and extract local and global image features. This feature set $\underline{f}$ typically includes relations among structural components of the image such as points, lines, and areas, as well as quantitative parameters attached to them. In reality there is a continuum of possible image features and their transformations, and their choice depends on the purpose and requirements of their subsequent use or interpretation. The image feature set $\underline{f}$ provides the basis for an *image-based* observer and associated feedback control structure. At a higher level, the image feature set $\underline{f}$ may be used to interpret the observed scene. Such an interpretation requires the recognition of objects in the scene and the estimate of object relations in the world coordinate frame. The output of this *recognition observer* is an estimate of $\hat{\underline{X}}_{rel}$ of the relative position of camera and object, and may be used in a sensor-based feedback controller based on world coordinate reference signals $\underline{X}_{rel\text{-}ref}$. Such a recognition observer depends on transducer, object, and scene models for its interpretation, and may introduce complex forms of measurement noise as well as time delays into the feedback system.

Figure 2-1 shows a simple example of a visual servo control structure based on the recognition observer. This system is called a position-based "static look and move" structure for visual servo control and is used most often in present industrial applications[6,7,8]. The system operation consists of a sequence of independent steps:

1. Step 1: The vision system "looks" at the scene, or object, and estimates the relative end-effector position $\hat{\underline{X}}_{rel}$. In current applications the recognition and position measurement phases are relatively simple due to the highly structured environment.

2. Step 2: The position estimate is sent to a task computer. The task computer computes the difference, $\Delta\underline{X}$, between where the end-effector should be, $\underline{X}_{rel\text{-}ref}$, and the current position estimate. The task computer then issues a command to an independent closed-loop robot positioning system[2] to "move" by the incremental distance $\Delta\underline{X}$; and

3. Step 3: The robot moves to the new position. Step 1 is not repeated until the robot completes the motion

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[2] The closed-loop robot positioning system includes dynamic joint servo controllers, and kinematic decoupling software which allow movements to be specified in world or tool coordinates.

specified by the "move" command.

If the combined accuracy of the robot positioning and vision measurement systems are within the allowable tolerances of the task, then this sequence need only be executed once. However, if improved accuracy, noise reduction, rejection of external disturbances, or tracking of a moving object is required, then the sequence of operations is repeated until a specified accuracy is achieved. The "static look and move" structure demonstrates the concept of interactive sensing for robot positioning, but is not a *dynamic* control system since each step is executed independently and in sequence. Thus, the dynamics of each operation at each level of the hierarchy do not affect the overall system stability.

In contrast, if the visual feedback system is structured so that the three steps outlined above are executed in parallel (i.e., positions estimates, $\hat{\underline{X}}_{rel}$, and position errors, $\Delta\underline{X}_{rel}$, are updated as fast as they are measured, and position corrections are commanded to the robot while it is moving), then the dynamic interaction between the levels of the hierarchy becomes critical. Using this approach, dynamic visual servo control systems can be synthesized[4, 1, 9, 10]. The role of computer vision as the recognition observer affects the overall system dynamics, and a visual feedback controller is required for stability and to achieve acceptable transient response (Figure 2-2). The linearity, noise properties, coupling, and computational delays of this measurement process become essential considerations for controller design. Formal analysis and design of feedback controllers for visual servoing using principles of control theory has not appeared in literature except for a simple case[10]. Most visual servo controllers have been designed using ad-hoc strategies[4].

This dynamic feedback strategy may further be generalized to control the open-loop robot dynamics and kinematics directly and eliminate the "arm-solution" required by the closed-loop robot positioning system This position-based visual servoing structure may have potential advantages including elimination of added computational delay, required by the "arm-solution" evaluation period, and elimination of "arm-solution" modeling inaccuracies. The feedback controller must compensate for any nonlinear and coupled robot dynamics and kinematics, as well as measurement delays and noise. While Koivo[11] and Takegaki[12] did not mention visual servoing, they did propose adaptive feedback controllers for such combined dynamic and kinematic control. And, Khatib[13] proposes task level "operational space" (positional) control, using visual feedback, based on a nonlinear feedback controller.

Dynamic control has the potential to achieve faster responses than "static" systems and dynamic considerations will become

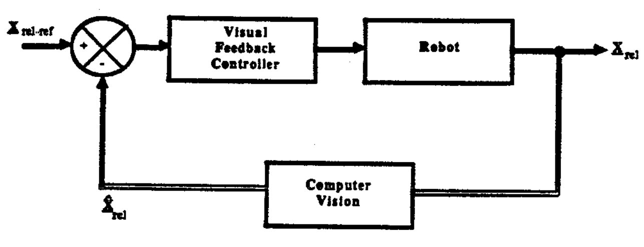


Figure 2-2: Dynamic Visual Servo Control

increasingly important as vision processing becomes faster and task representations more demanding. Dynamic visual servo control presents a variety of difficult design problems which are not currently addressed in the literature, including a formal approach to controller design and complexity of the feature-based or recognition observer. An adaptive image-based control approach to this problem is described below.

# 3. Imaged Based Control

In the position-based control approaches, the vision system is used as a recognition observer to measure the relative positions $\underline{X}_{rel}$ between the robot end-effector and some object in it's environment. This measurement process can be decomposed into two nonlinear transformations. First, the transduction and feature extraction functions, or world-to-feature space transformation, can be viewed as the inverse of an ideal interpretation, in the absence of noise, according to:

$$\underline{f} = I^{-1}[\underline{X}_{rel}] \tag{1}$$

where $\underline{f}$ are the features and interpretation I is "ideal" in the sense of being based on exact object and image transducer models. Second, the features are mapped to world space by the approximate interpretation transformation:

$$\hat{\underline{X}}_{rel} = \hat{I}[\underline{f}] \tag{2}$$

where, modeling inaccuracies and image transducer noise lead to equivalent measurement noise. If the interpretation has a unique inverse mapping, over the control region of interest, such that $\underline{X}_{rel}$ are single-valued functions of $\underline{f}$, then this suggests that the system can be controlled, to unique end-points, using features directly as the feedback and reference signals, thus eliminating the interpretation step (2). The uniqueness condition is satisfied, for the control region of interest, when[14]:

1. The first partial derivatives of $\underline{f}$ are continuous, and
2. If the Jacobian of the ideal inverse interpretation is nonsingular; i.e.,

$$\det[J_{feat}] \neq 0 \tag{3}$$

where $J_{feat}$ defined as the feature sensitivity matrix is:

$$\det \frac{\partial I^{-1}[\underline{X}_{rel}]}{\partial \underline{X}_{rel}} \doteq J_{feat} \tag{4}$$

In practice, $J_{feat}$ could be estimated on-line to test the condition in equation (4). This condition must be true for both position and image-based approaches. Further, since the determinant is only defined for square matrices, then the permitted number of degrees-of-freedom must equal the number of measured features.

A digitally controlled image-based visual servo (IBVS) control structure, which uses feature feedback, is represented in Figure 3-1. This system was first proposed by Sanderson and Weiss[15]. In such an IBVS system, the reference and feedback signals are defined in terms of the image feature values corresponding to the current and desired robot positions. The feature errors may be derived at every measurement time and used to drive the robot in a direction which decreases the error. In Figure 3-1, $\underline{u}$ are the control signals, $\underline{q}$ are the generalized robot joint coordinates, and $n_d$ is the number of feedback delays

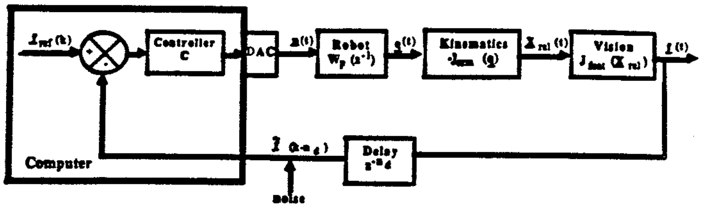


Figure 3-1: Image-Based Visual Servoing

introduced by the vision processing. Image-based structures which incorporate inner closed-loop positioning control, such as in the position-based "look and move" structure, can also be derived.

In image-based control, reference signals, $\underline{f}_{ref}(k)$, must now be defined in feature-space. To accomplish this, the task could first be defined in world space, $\underline{X}_{rel\text{-}ref}$, and then mapped into $\underline{f}_{ref}$ according to an idealized inverse interpretation (1). Equivalently, if $J_{feat}(\underline{X}_{rel})$ is known, or can be measured, and the initial displacement $\underline{X}_{rel}$ is known, then the feature signal can be derived by evaluating the feature sensitivity matrix along $\underline{X}^{o}_{rel} + \delta\underline{X}_{rel\text{-}ref}$ according to

$$\delta\underline{f}_{ref} = J_{feat}\,\delta\underline{X}_{rel} \tag{5}$$

While both approaches still require an interpretation procedure to recognize the features and to derive the transformations, they may offer potential advantages by eliminating inaccuracies of the actual interpretation, in the feedback path, and by requiring smaller sampling periods as a result of the elimination of the feedback interpretation delay.

An alternative approach, which only requires an interpretation procedure for feature recognition, is to define the reference signal directly in image feature space using a "teach-by-showing" strategy. In this approach, an image is transduced in the desired reference position and the corresponding extracted features represent the reference features. For repetitive tasks, with known world coordinate trajectories, the reference feature signals can be defined apriori as a "moving" or time-varying image along the path. In an unstructured task environment, only the final or desired feature values can be defined, and world coordinate trajectory cannot be directly controlled. The most useful applications of teach-by-showing image-based systems might be for tasks requiring fast and accurate corrective motions, where exact path is not critical (e.g., for precision assembly including random part acquisition and parts alignment). While the path cannot be directly controlled with the "teach-by-showing" strategy, we show that if the coupled feature sensitivity matrix $J_{feat}$ is constant, and each feature is specified to have identical dynamical time responses, the predicted path is straight-line, irrespective of the number of degrees-of-freedom. In addition, our simulation studies show smooth paths are achieved over a wide variety of system and parameter situations, including for highly coupled and time-varying sensitivities $J_{feat}$. The "teach-by-showing" approach presents additional requirements for controller design. In this approach, it is assumed that the inverse transformation $I^{-1}$ is unknown. Therefore, the feedback controller must be based on a design approach which not only compensates for the nonlinear and coupled properties of $I^{-1}$, but also for unknown values.

# 4. Control of Image-Based Systems

The analysis, design, and evaluation of image-based systems has been studied by Weiss[16]. To design an image-based controller, it is useful to first consider the small-signal model (i.e., about a nominal operating point or trajectory) of an the IBVS structure in Figure 3-1. The control signals are applied through digital-to-analog converters (DAC) which can be modeled by the cascade of an ideal impulse sampler and a zero-order hold with a saturation nonlinearity[17]. The system output is the undelayed feature, while the feedback path is modeled by discrete unit delays. Linearized open-loop robot dynamics[18], or equivalent linear I/O models[19], are represented by the discrete-time Z-transformation $W_p(z^{-1})$. The feedback path is characterized by an overall small-signal sensitivity matrix J given by

$$J \doteq J_{feat}\, J_{arm} \tag{6}$$

where $J_{arm}$ is the kinematic arm Jacobian. In addition to the control requirements of the robot dynamics, the design of the controller C also depends on the "J" sensitivity matrices, feedback delays, and measurement noise. The sensitivity matrices are nonlinear and coupled functions of $\underline{q}$ and $\underline{X}_{rel}$; thus, J varies as $\underline{q}$ varies, and feature-space transformations are manifested by time-varying open-loop gains. Predicted values of J can deviate from actual values due to inaccuracies in the modeling of the three dimensional object and transduction process, and from drift and variation in the transducer parameters. At the extreme, the values may be completely unknown apriori when minimal knowledge of the inverse interpretation transformations $I^{-1}$ are available, such as arises when task programming is limited to the "teach-by-showing" strategy. Fixed feedback controller designs have limitations in the control of such *nonlinear* and *unknown* systems. Even if the nonlinearities are known, a fixed controller design for these systems is a formidable engineering problem. In contrast, an adaptive approach to controller design appears to be applicable for these requirements. The IBVS controller design used in our research therefore emphasizes the adaptive approach.

## 4.1. Adaptive IBVS Control

In the context of joint-level control, a few researchers have evaluated the potential application of adaptive control to robotic manipulators[18, 20, 21, 22, 23, 24]. Adaptive control has the potential to compensate for parameter uncertainty and variation over a wide range, while operating at high joint speeds. In these adaptive control schemes, an adjustable controller uses on-line identification to identify parameters of an equivalent input/output (I/O) linear model of the robot based on the I/O information vectors $\underline{u}(k)$ and $\underline{q}(k)$ (i.e., actuator control signals and joint positions respectively), under the assumption that the robot is linear and constant, but has unknown parameters. An equivalent I/O model is one that predicts the output $\underline{q}(k)$ from past and present I/O information independent of the physical model of the robot. The estimated parameter values are then used in a linear feedback controller as though they where the actual parameters.

The mathematical basis for our adaptive controller follows the enhanced identification error model reference adaptive control (MRAC) developed by Morris and Neuman[25]. While similar approaches have appeared in the literature, their research focused on details of physical implementation including control signal saturation and controller stability, measurement noise,

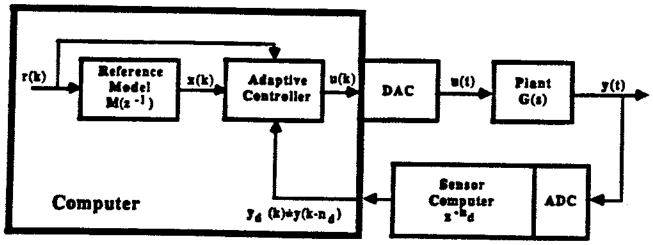


**Figure 4-1:** Model Reference Adaptive Control

and computational complexity for microprocessor implementation. Since the algorithm did not include control of systems with discrete measurement delays, we have extended it to include control of systems with delay[16]. Additional modifications for applying uncoupled MRAC to the control of coupled nonlinear systems were also developed.

In joint-level MRAC control (Figure 4-1), the reference model output $\underline{g}^R(k)$ specifies a stable and realizable closed-loop dynamic response of the the output $\underline{g}(k)$ to the reference signal $g_{Ref}(k)$. The difference between the reference model output and the process is called the full-parallel (FP) output error:

$$\underline{e}_o^{FP}(k) = \underline{g}^R(k) - \underline{g}(k) \tag{7}$$

The adjustable controller utilizes the identified parameters information to adjust the gains on-line to drive the FP error to zero, thus forcing the robot output to track the reference signal in accordance with the performance specified by the model. In the identification-error method of MRAC control[24] an identifier predicts the robot joint outputs, $\underline{t}(k)$, based upon parameter estimates of an equivalent linear I/O model. The identification error

$$\underline{e}_{ID}(k) = \underline{g}(k) - \underline{t}(k) \tag{8}$$

drives the adjustment mechanism which updates the estimates of the equivalent parameters. These estimates are then used to adjust the gains of a linear controller which is driven by the model output. The adjustment mechanisms can be designed from either parametric optimization or stability viewpoints.

Both single-input single-output (SISO) and multiple-input multiple-output (MIMO) equivalent model formulations can be used to derive the adaptive controller. In the context of joint-level control, Neuman and Stone[26] have justified the latter modeling approach by demonstrating that individual joints of a coupled and nonlinear robot can be modeled by linear time-varying second-order SISO transfer functions. They show that the transfer function parameters vary smoothly in the work space as a function of the joint positions, velocities, and accelerations. While coupled, or MIMO, controllers have an inherently greater potential for being able to uncouple a coupled system they have several potential disadvantages, including computational complexity and they do not lend themselves to modularity. A modular system can easily be extended to increasing degrees-of-freedom, and distributed processing. Uncoupled adaptive controllers have already demonstrated the potential to control dynamically coupled robots[23, 24], and would be easier to implement in current laboratory and factory computing environments. For these reasons, the approach which we developed emphasized uncoupled control of coupled systems, using the concept of equivalent SISO plants. For example, a two degree-of-freedom (DOF) IBVS system is controlled by independent MRAC controllers in Figure 4-2.

### 4.2. Feature Selection and Assignment

Feature transformation coupling (i.e., represented by the small-signal feature sensitivity matrix **J**) leads to related problems of feature selection and assignment. Feature selection requires a subset of n features be selected from a set of m possible control features $f_i$ ($i = 1, \ldots, m$), where $m > n$. Feature assignment addresses the choice of which feature should be used to control each actuator. Both issues are related to the degree-of-coupling of the feature transformation. We have developed a measure of coupling to address these issues.

#### 4.2.1. Feature Assignment Using Diagonal Dominance

In applications where uncoupled controllers are used to control coupled plants, there is always the problem of choosing which servo error will control which actuator; that is, for a set of n outputs $y_i$ ($i = 1, \ldots, n$), which servo error, $\Delta y_i$, should be filtered and coupled to the $j^{th}$ actuator as $u_j$? To formalize this assignment procedure let the open-loop linear system be defined by

$$\underline{Y}(s) = H(s)\underline{u}(s) \tag{9}$$

where H(s) is an (n x n) transfer function matrix. When the system is uncoupled, H(s) can be transformed into a diagonal matrix by switching the $j^{th}$ and $k^{th}$ columns of H(s), and therefore the $j^{th}$ and $k^{th}$ rows of $\underline{u}(s)$, until all off diagonal elements of H(s) are zero. When H(s) is diagonal, the only

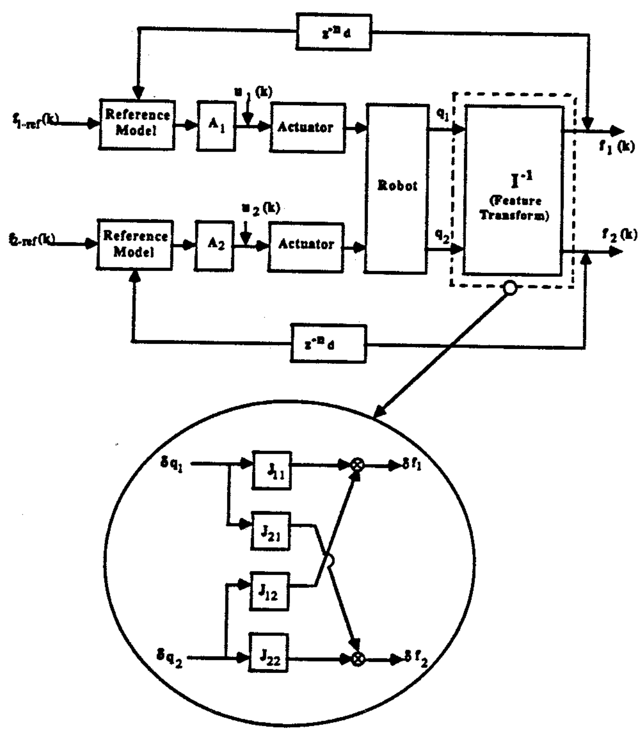


**Figure 4-2:** MRAC Control of an IBVS System

choice for servo error/actuator assignment is $u_i \leftarrow \Delta y_i$. When the system is coupled, then H(s) cannot be transformed into a diagonal matrix. Servo error/actuator assignment can be accomplished by organizing H(s) in a "diagonally dominant" fashion[27], such that the diagonal elements dominate the off-diagonal elements. Diagonal dominance is defined as

$$|H_{ii}(s)| > \sum_{\substack{j=1 \\ j \neq i}}^{n} |H_{ij}(s)| \quad \text{for } i = 1, \ldots n \tag{10}$$

When H(s) can be organized according to this definition of dominance, then limited stability properties of both coupled and uncoupled fixed control of the system can be formulated[27]. When applied to image-based systems, with $|JW_p| \leftarrow H(s)$, we have shown that the sensitivity matrices cannot in general satisfy this definition of dominance.

An alternative approach is to organize $JW_p$ to maximize the inequality (10) over all possible column arrangements. This criterion reduces to defining the dimensionless measure of diagonal dominance as

$$D(k) = \log \sum_{\substack{i=1 \\ j \neq i}}^{n} \sum_{j=1}^{n} \frac{|JW_{p\text{-}ij}(k)|}{|JW_{p\text{-}ii}(k)|} \tag{11}$$

and then minimizing $D(JW_p)$ over all n! possible column arrangements. The logarithm of the dominance is used since the ratios change by orders of magnitude.

### 4.2.2. Feature Selection

The image of a typical scene contains more features than there are degrees-of-freedom to control. The number of features must equal the number of degrees-of-freedom in an image based system since the feature sensitivity matrix is constrained to be square. The possible number of ordered candidate feature subsets is

$$p(m,n) = \frac{m!}{(m-n)!} \tag{12}$$

where ordering is required to consider the feature/joint assignment.

To arrive at a criterion for feature selection, two aspects of feature-based control are analyzed:

1. Ability to specify world space path using feature based trajectories (assuming that the control system can achieve a specified feature space performance), and

2. The control effort required to achieve the specified feature space dynamic performance.

It is shown below that the attributes of the feature sensitivity matrix, $J_{feat}$, relate to path performance, while the attributes of $JW_p$ relate to the control effort aspects.

With respect to world space path, it is desirable to be able to control each world level DOF independently. To achieve this goal, an ideal subset of features should yield a feature sensitivity $J_{feat}$ which is diagonal and constant. Then,

$$\Delta X_i = \frac{\Delta f_i}{J_{feat\text{-}i,i}} \tag{13}$$

where, $\Delta X_i$ is the path error for the $i^{th}$ DOF, $\Delta f_i$ is the $i^{th}$ feature error, and $J_{feat\text{-}i,i}$ is the $(i,i)^{th}$ element of $J_{feat}$. If straight-line motion is desirable, and all of the features exhibit the same dynamic response, then straight-line motion would be achieved. For example, assume that the $i^{th}$ feature response is specified by the critically damped response

$$f_i^{\circ}(t) \doteq f_i(t) - f_i(0) = \Delta f_i (1 - e^{-t/\tau}) \tag{14}$$

and all feature responses have the same time constant $\tau$. The response of the $i^{th}$ DOF is

$$X_i^{\circ}(t) \doteq X_i(t) - X(0) = J^{-1}_{feat\text{-}i,i} f_i^{\circ}(t) \tag{15}$$

The relationship between any two Cartesian degrees-of-freedom becomes

$$\frac{X_i^{\circ}}{X_j^{\circ}} = \frac{J^{-1}_{feat\text{-}i}\ \Delta f_i}{J^{-1}_{feat\text{-}j}\ \Delta f_j} \frac{1-e^{-t/\tau}}{1-e^{-t/\tau}} = \text{Constant} \tag{16}$$

which is constant and specifies the equation of a straight-line in Cartesian coordinates. It thus becomes straightforward to specify straight-line motion.

If an ideal feature sensitivity matrix could be synthesized, then it still remains to control dynamically the system to achieve the desired feature response. Attributes of the overall sensitivity, $JW_p$, can be used to describe the control effort required to achieve the desired response. Similar to the feature sensitivity attributes, the idealized overall sensitivity matrix should be diagonal and constant. Diagonalization permits the unqualified use of independent SISO controllers. In our experience, these idealized sensitivity attributes cannot be expected in practice. The degrees-of-freedom are coupled and the sensitivities typically vary with position. Feature sensitivity changes are minimized for small motion tasks, and for configurations with large lens magnifications. However, if the feature sensitivity were constant, but coupled, the predicted path would still be straight-line motion irrespective of the number of degrees-of-freedom. Since

$$\underline{X}^{\circ} = J^{-1}_{feat}\, \underline{f} \tag{17}$$

then

$$X_i^{\circ} = (J^{-1}_{feat\text{-}i,1} \Delta f_1 + \ldots + J^{-1}_{feat\text{-}i,n} \Delta f_n)(1-e^{-t/\tau})$$

$$= K_i (1 - e^{-t/\tau}) \tag{18}$$

where $K_i$ is a constant. The constant relationship between any two Cartesian DOF becomes

$$X_i^{\circ}/X_j^{\circ} = K_i/K_j \tag{19}$$

which is the equation of a straight line.

Since we may not expect to find feature subsets which yield idealized sensitivity attributes, a feature selection strategy could seek a subset which best approximates these ideals; i.e., select features which minimize the coupling and sensitivity changes along a trajectory. In our research, the diagonal dominance measure, $D(JW_p)$, in eq.(11), is used to quantify system coupling. The feature selection strategy then becomes minimizing $D(JW_p)$ and $D(J_{feat})$ over the set of candidate features. By minimizing $D(JW_p)$, improved dynamic response is achieved with SISO controllers. And, by minimizing $D(J_{feat})$, closer to monotonic path performance may be expected. Each strategy may not produce mutually exclusive decisions, and arbitration between them would be based on the relative importance of each attribute. For example, a system could be feature uncoupled in the joint space of an articulated robot arm, but not uncoupled in Cartesian space. Since the degree-of-coupling plays such an important role in the independent control approach, our research focused on evaluation of feature selection based on minimization of $D(JW_p)$.

Extensive simulation studies have been completed for one, two and three DOF systems, and preliminary results are available for a 5 DOF system. These experiments are described in detail in the cited references[16], and the results are summarized below. Performance limitations and application of fixed controllers were also evaluated using linear model following controllers (LMFC)[28]. Each LMFC is derived by fixing the gains of the adaptive controller to values derived from initial learning trials in the simulation experiments. We show that, a fixed controller tuned for one task may not be suitable for another task. However, a single adaptive controller is suitable for a range of tasks. Fixed controllers are suitable for tasks with small sensitivity changes (e.g. tasks requiring small corrective motion). While adaptive control is superior for large motions, we demonstrate that fixed controller performance exhibits superior noise performance and superior stability at lower sampling-to-bandwidth ratios. Tasks which use either Cartesian manipulators or articulated arms, and which require small motions (e.g. on the order of magnitude one to two inches), can be controlled using the multiple SISO controller approach. However, for tasks using an articulated arm and requiring larger motions, the additional kinematic coupling leads to unacceptably large path deviations with either adaptive or fixed SISO controllers. These systems would require a coupled controller. With respect to the predicted paths, we show that smooth pathes, which approach straight lines, can be achieved for configurations with highly coupled and nonlinear sensitiviies $J_{feat}$. Finally, exhaustive testing shows that both path and dynamic performance improve as the coupling index decreases.

## 5. Discussion

In this paper we have described a hierarchical robot control structure with multiple observers, and have pursued the analysis and simulation of a feature-based observer for visual feedback control. Evaluation of this adaptive image-based visual servo control strategy suggests that such systems may provide speed and accuracy improvements with simplified implementation. The feature-based strategy does not explicitly control position trajectories but may be regarded as an inherent strategy for real-time trajectory planning. The feature-based observer is useful in regimes of motion where image features have well-defined relations to the task. Such regimes must be monitored by a recognition observer within the hierarchical control structure. In a variety of applications this complimentary relationship between feature-based and recognition observers occur naturally in the task definition. In mobile robot navigation, for example, local features may be effectively used for real-time control, while global scene interpretation occurs at a much slower rate. Control of dexterous hands using finger-tip tactile arrays is another case where local or feature-based control may be used in a complimentary fashion with a more global recognition observer to achieve complex manipulation capabilities yet maintain dynamic performance. The development of an adaptive IBVS controller in should provide insight and analytical tools for the analysis, design, and evaluation of dynamic sensor-based robot control systems, and may serve as an example of a feature-based observer with broad application to hierarchical sensor-based systems.

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