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Gaze Controls with Interactions and Delays

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Abstract —**Complex autonomous sensorimotor behavior can be constructed from simple behaviors, whose interaction then poses technical questions. Multibehavior control is explored in a simulation of gaze control using saccadic, vergence, pursuit, vestibulo-ocular reflex (VOR), and head control. Prediction (kinematic for the agent, dynamic for world objects) overcomes time delays, saturation, and behavior interactions.**

I. Cooperation in Low-Level Behaviors

Systems that behave in the world are becoming increasingly sophisticated, raising technical problems of sensing and control and opening new approaches that may make perception easier. One of the goals of artificial *animate vision* [4], [5] is to exploit the ability to maneuver in 3 D to make some vision problems easier. Another goal is to design a systems architecture in which multiple objectives (such as moving and observing) can proceed in parallel. One common premise is that cognitive processes at high abstraction levels rely on a hierarchy of lower level "skills," "reflexes," "behavior," and active vision capabilities that autonomously keep the agent out of trouble and perform generally useful vision computations [11]. Another premise is that active control over and perception of an agent's own state (*proprioception*) makes many problems in perception, planning, and acting easier [1].

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This paper is an investigation of a mechanism (based on prediction) for coordinating multiple behaviors based on perceptual input. The behaviors take place in the domain of gaze control. The main conclusion is that autonomous, mutually independent behaviors seem unsatisfactory to implement gaze control, but that a predictive ability for both agent and world states solves many problems caused by interaction and delay.

A *gaze control* system manages several basic, interacting head, eye, and even body motion capabilities, with the aim of supporting purposeful (or default) activity. One basic activity is the visual *acquisition* of an object. The action can be reflexive, in response to a stimulus deemed interesting, or under control of a higher level engaged in planning or acting. Another basic ability is to *pursue* or track an object moving relative to the observer: stabilization of the image on the sensor is necessary for high resolution imaging, and the resulting proprioception (i.e., motor commands that effected the tracking) provides information about object motion. From the point of view of control theory, a gaze control system has two main *technical problems*: the *interaction of component subcontrols* and *delay*. Both biological and robotic systems can easily have delays that are of the same order of magnitude as the timescale of the actions.

Gaze control mechanisms have long been studied in biological systems (there are extensive references in [8], [19], [31]). Much of the work concentrates on how biological systems solve the two basic technical problems mentioned above. This paper investigates predictive mechanisms as a solution for the problems primarily in a robotic context, but occasionally relates the results to some findings and theories from primate gaze control.

One way to cope with delays is to use strictly open loop control. The other approach, more common in engineering applications, is to use *predictive* and modeling techniques to anticipate the state of the plant, its input, and indeed the world [25], thus coping with both delays and interactions. *Smith's principle* [36], [37] is the basic tenet that the desired output from a controlled system with delay T is the same as that desired from the delay-free system, only delayed by T. The principle leads to several techniques for controlling delayed systems. Smith's principle may be coupled with *signal synthesis adaptive control* [3], which predicts object motion to allow more accurate responses. Kinematic and dynamic models for plant prediction can be known *a priori* or derived from learning and used to replace feedback [23]. The solution described here uses Smith's prediction to integrate multiple controls with delays. It uses signal synthesis adaptive control with flexible and general techniques of *kinematic simulation* to predict the state of the plant and variance-minimizing *optimal filtering* to predict the state of the world. At least in simulation, the resulting predictions have three effects. *Delays are overcome, interactions are overcome, and performance is improved*. Predictive techniques seem to form a sound basis for the design of integrated, high performance sensorimotor systems.

II. The Model of Head and Imaging

The model of head and binocular imaging presented here is relatively general and parameterizable, and in particular captures all the essentials of the Rochester robot [12], [14]. This device has a three degree of freedom binocular head (one tilt platform, independent pan axes) mounted on a six degree of freedom industrial robot arm. It has been used to demonstrate various low-level real-time active vision capabilities [6], [28]. In the work reported here, the head kinematics are modeled but the robot kinematics are not: the model abstracts the arm to a single "head" coordinate frame that can be positioned arbitrarily in

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space with six degrees of freedom (in fact the robot control software supports this abstraction as well). The simulated mechanism is massless; this reflects the effective behavior of our current hardware system when viewed from its high-level control operations. In fact, as in most industrial arms, the joint controllers keep motion slow enough that dynamics is irrelevant. For high-speed applications, more sophisticated robot control is needed (as in [2], for instance), which in turn would call for a more sophisticated simulation. The independent control of the camera pans permits modeling of modern physiological theories of eye dominance in saccadic and vergence systems and to explore the control of independent eyes. Heads with mechanical vergence capability need one less motor and are thus lighter but are less flexible.

The target is a single point in 3-D space, moving under dynamical laws. The experiments were carried out with the target undergoing elliptical or straight line motion. In some of the experiments involving delays the target was stationary but the robot moved in X, Y, and Z, thus creating a perceived target motion, but one due to factors under robot control.

The camera model incorporates point projection with fixed focal length. The simulated left or right image of the target is simply its (x, y) image position. It is assumed that the agent can compute the distance to the target (using binocular stereo, *a priori* knowledge, monocular distance cues, or kinetic depth calculations). It is assumed that, for each eye, the instantaneous retinal velocity of the target is known (i.e., the vector difference between its position in the current image and its position in the last image). The camera model has a "foveal-peripheral" distinction by which the location of imaged points is less certain, outside a small foveal region, depending on the off-axis angle of the target being imaged. There is a further provision for sensor noise, to model quantization noise, or for used of approximate process noise in the target's motion.

III. Comparison with Primate Gaze Control Models

Because of its experimental accessibility, the simplicity of the plant involved, and the diverse collateral knowledge about the visual system, the gaze control system is the best-studied biological sensorimotor control system. The animal model most relevant to our robotic work is the primate, because of the close relationship of visual attention with fixation that arises with foveal (i.e., narrow-angle, high-resolution) vision. Gaze control in the cat and rabbit (and frog) is significantly different.

Knowledge of the primate gaze-control system might help provide insight to robot designers, and if the right hardware were available robotic equipment might be used to implement computational models of gaze control, thus providing an experimental facility complementary to the usual psychophysical and neuroscientific ones. The work described here is not yet dedicated to modeling biological systems, but nonetheless comparisons are inevitable, amusing, and possibly useful. This section is a very brief and admittedly selective sampling from the immense and rich (i.e., confusing and contradictory) literature on gaze and head control in biological systems. Most of these systems interact, and it is very difficult to lay down hard and fast rules about what individual systems can and cannot achieve.

A. Pursuit and Opto-Kinetic Reflex (OKR)

The opto-kinetic reflex (OKR) causes the eyes to follow a motion of the full visual field, and is driven (to first order) by "retinal slip," or optic flow. In primates the OKR comes in two stages, a faster (direct) and a slower (indirect), with the direct being more dominant in man. The smooth pursuit mechanism is to track small targets, and is often described as being driven by foveal retinal slip. Thus these two facilities are similar, and there is some thought that the direct part of the OKR response is just the smooth pursuit system [16].

The situation with smooth pursuit is anything but simple, however. It seems to be possible to pursue extra-foveal targets smoothly. Smooth eye movements cannot normally be induced without a smoothly-moving stimulus, but they persist after a target disappears, thus arguing that some form of prediction can excite the response [17]. Smooth pursuit gain drops with stimulus velocity. Last, smooth pursuit in monkeys seems to be driven (in a large fraction of individuals) not just by velocity error but also by position and acceleration errors. Thus a model such as Young's (Section III-E) that suggests a reconstructed target velocity is the control input (rather than a sensed optical flow) could be augmented with a broader range of error signals [24].

B. Vergence and Saccades

The primate vergence system is rather slow, and coupled to the focussing (accommodative) systems and the saccadic system. Vergence and accommodation are coupled pairwise, and the "near triad" is a reflex made up of these three systems, in which focus and vergence are both driven in the proper direction and faster than normal when a saccade from close to distant target (or the reverse) is made [26].

Work with the Rochester robot has concentrated on "gross vergence" mediated through disparity computed between full-field images with variants of the cepstral filter [28]. The simulator described here is driven by horizontal disparity between the left and right target images. In the simulator, (which does not include focus) the cooperation of vergence and saccades is achieved simply, by the device of letting imaging, disparity calculation, and vergence reflex run during saccades. This method may or may not be nonbiological (as usual there is some dispute about the amount of visual processing that goes on during saccades). Its practical disadvantage is that it is inefficient: it is no harder to have the saccade control both eyes. The work here, however, assumes a vergence behavior that can operate during saccades.

The saccadic system has a longer delay than smooth pursuit (120 ms as opposed to 50 ms), reflecting its higher level control origins. It can move the eye at 300 to 400 deg/s. It is often modeled as a sampled-data system, kept stable by a latency and trigger mechanism that inhibits its firing again before the system has settled. In the robot system, saccades may not be needed for position control during tracking, and thus will mainly be associated with shifts of attention, or at least of visual resource commitment.

The experiments described here use a strictly "left eye dominant" model of control—saccades and tracking only affect the dominant (left) eye, and vergence controls only affect the other eye. This is almost certainly an exaggeration of the ocular dominance effects in primates. From a practical point of view it means that the necessary low-level vision computations do not need to be carried out in both eyes simultaneously.

C. The Vestibulo-Ocular Reflex (VOR)

The vestibulo-ocular reflex (VOR) stabilizes gaze by counteracting commanded head movements with eye movements. It is the fastest visual reflex, with a delay of only approximately 16 ms. It is an open-loop control, in the sense that vestibular sensor output is converted to eye muscle input and delivered through a path of approximately three synapses. It can be a high gain control (gain approximately 1): it can often exactly cancel out head motion effects. The VOR being open loop, there is a general problem of how it internally models the system it is controlling.

Research on the VOR has addressed the geometrical aspect of its modeling: the conversion of sensor signals in the coordinate systems of the semicircular canals to effector signals for the variously-placed eye muscles. Robinson [33] models the geometrical transformations as 3 by 3 matrices operating on 3-vectors. Changing matrix components can accomplish adaptation, and the adaptation can be driven by stimuli such as retinal slip (indicating a failure of the reflex) without explicitly modeling the sensorimotor system. Pellionisz [29], [30] uses tensors to model the differing transformation properties of the sensory and motor vectors and transformations, and addresses the problem of underdetermined control of the many muscles that accomplish eye and head movements by the relatively small number of sensor dimensions.

The VOR's input originates in the linear and angular accelerometers of the otolith organs and semicircular canals. They have very short time constants, but the VOR operates correctly for slow velocities. This leads to the postulation of a "velocity storage mechanism" that integrates the output of the accelerometers and makes the resulting velocity signal available for control (e.g. [32]).

Other VOR work addresses its time-dependent behavior: its gain and phase-lag characteristics under different conditions (e.g., several papers in [8]). Much of the VOR's behavior can be explained as parameter variation among its gain, bias, and time constants. Miles *et al.* [27] developed a multichannel model to explain VOR's ability to cope with the frequency-dependent output characteristics of the sensors, with frequency-selective adaptation properties of the VOR itself, and with other adaptive properties of the VOR. This paper presents explicit transfer functions for the semicircular canals, the oculomotor plant, the velocity storage mechanism, and the neural channels that convert head velocity estimates to motor outputs. The channel model is linear and can be stated as a lumped-parameter linear system, but the channels make it easier to identify which gains must be changed to reduce system errors.

A basic aspect of the VOR is its adaptability. The reflex adapts over time to changes in the optical system (e.g., artificially induced dysmetria) [33]. The VOR interacts with other reflexes and the stimuli that evoke them. For example, large-field rotations that elicit the OKR have an interesting effect. If they are slow, they bias the VOR (and the opto-kinetic system) in the same direction, which tends to cancel the movement effect. If they are fast, they induce effects in the opposite direction, which may be interpreted as ignoring the movement effect [16]. VOR gain can be depressed from 1.0 to 0.1 by training that involves no visual input (subject imagines tracking a target attached to head while moving head in the dark), and is likewise significantly affected by verbal instructions and other seemingly unrelated activities (such as mental arithmetic) [22].

Adaptation and modeling can come together in VOR behavior that adapts to repetitive patterns (perhaps a familiar example is disembarking from a long sailing journey). One way to achieve this capability is through a "pattern storage" mechanism that effectively produces and uses a model of the outside world. Some workers are attracted to this idea, others seem to think it is unnecessary and the data are explicable by, for instance, channel adaptation.

With a robotic VOR, many of these issues can be avoided. The relation of the sensor output to the desired motor output can be known accurately through an accurate kinematic model. (In fact in the simulation of this paper, the robotic VOR makes several approximations, including a simplified geometry for the camera rotation axes, a small-angle approximation, and others.) Velocities may be directly sensed, and "efferent copies" of control signals are easily obtained. The fundamental issues that still need significant work involve adaptation and interaction. Adequate understanding of these issues would not only give the robot system the efficiency exhibited by natural systems, but could mean that such exercises as accurate kinematic modeling would become unnecessary.

D. Head Control

There is less written on head control than on gaze control, but a good recent collection of work exists [31]. There are various head stabilization reflexes, some tied to optical stimulation. The relation of head control strategies to the evolution of particular brain mechanisms and the existence of foveate vision is explored by Roucoux and Crommelinck [35]. Some fairly detailed biomechanical head models exist, and head movements have been investigated from the point of view of optimal control theory. Head movements can be quite rapid (600–700 deg/s) and are part of normal long-distance saccades in primates. Thus the saccadic and head control system work together to achieve gaze redirection. There has been some work here (e.g., [21]) indicating that head movements can take place at differing times relative to saccades. Typically, they lead or lag depending on whether the target location is predictable or not.

This coupling of head and eye movements is clearly more sophisticated than the compensatory reflex implemented in the simulation, which is not coupled to saccades at all and which must lag eye movements since it is only driven by eye positions. Thus more work needs to be done if we are to achieve the increased rapidity of gaze redirection that arises when both head and eyes are moved in a coordinated way.

E. Another Model of Delay Control

The control scheme implemented in this simulation, the Smith predictor, differs from a scheme seemingly first proposed in a gaze-control context by Young, taken a step further by Robinson, and used recently in robotic gaze-control for an agile, two-eyed robotic head at Harvard University [15].

Young [38] wanted to explain how smooth pursuit avoided instability in the presence of two difficulties that apply if tracking is modeled as a pure negative feedback system. First, the error, and thus the control, signal is zero when accurate tracking is achieved; this should send eye velocity transiently to zero. Second, tracking performance is better than it should be given the delays in the control loop and the time constants of the processes. His proposal is that the system tracks not the retinal image, but a neural signal that corresponds to target motion (in the world).

In 1971 (for a recent reference, applied to saccadic, tracking, and limb control, see [34]) Robinson proposed a mechanism to implement Young's idea. In the negative feedback system the eye velocity is fed back and subtracted from the target velocity (with some delay). If the eye is in the process of tracking, then the target velocity is the sum of the eye velocity (with respect to the head) and the target's retinal velocity (its velocity with respect to the eye). However, the latter is just the error signal resulting from negative feedback. Thus an estimated target velocity signal can be constructed by positively feeding back the commanded eye motion into the control loop, delayed to arrive at the proper time to combine with the error term produced by negative feedback. This mechanism not only provides a signal based on the target's true motion, but it cancels the negative feedback and thus removes the possibility of oscillations.

Robinson's scheme is related to the Smith controller shown in Fig. 1 in the following way. In Fig. 1, the signal at A is the retinal location of the object to be tracked. Its sign is changed at the first "summer" node to provide the error signal E. The signal at D is a difference of error signals that is zero when perfect tracking is taking place. This difference of errors is a delayed (but consistent) error signal that is added to the predicted error signal in the nondelayed path C. The controller in Fig. 1 tries to drive errors to zero. To change Fig. 1 to Robinson's scheme, delete path C and remove the modeled world and sensor from the lower half of the block diagram. Then path B carries the simulated plant, not the simulated error. Path E still contains error, but path D now contains a prediction, or reconstruction, of the world state. Thus the controller now must treat the signal at D as a set point to be achieved through open-loop methods, not as an error. Robinson proposes parametric adaptive control (in the form of two related

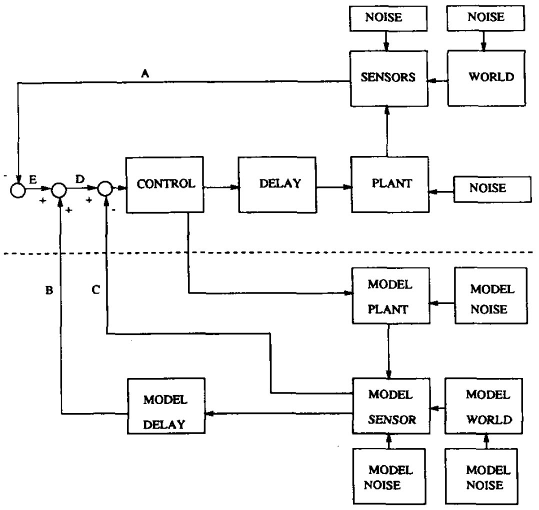


Fig. 1. The implemented Smith predictor control.

gains) to provide adaptative capability should the open loop yield the wrong results.

There are thus some similarities between the two schemes, but the underlying control philosophies are rather different. In particular, losing the power of negative feedback is a large sacrifice that the roboticist may not need to make. The Smith predictor control system keeps the advantage of feedback control (running on the modeled world and plant). There are many methods of estimation, observation, and prediction of world, sensor, and plant used in modern control theory, and thus the Smith model allows for flexibility in the assumptions underlying its predictions.

IV. The Model of Control

A. Zero Delay Control

The input to the control systems is usually based on quantities that can be inferred from vision (e.g., the (x, y) position of the target, which should be driven to (0,0), or target disparity between the two eyes which should be driven to 0). Some control inputs arise from the robot's "proprioception" (e.g., the amount the cameras are panned or tilted from their null position), and some is from other control signals (when one control is to null out the effects of another). The simulation has controllable output parameters corresponding to one set of VAL-II robot control parameters (the VAL-II "tool coordinate system" for the head: its X, Y, Z position and A, B, C orientation.) Also, there is direct control over the pans (independent for left and right) and tilt (common) of the two cameras. In every case the outputs of controls are velocity commands to the nine degrees of freedom in the system, reflecting one simple form of our current interface to the motor controllers.

The basic control loops that manage the system are loosely inspired by the primate visual system. However, most assumptions and technical decisions have been made either for the sake of simplicity or to mimic the Rochester robot rather than for the sake of faithfully modeling known biological systems or optimal mechanical systems. One of the major design goals is that the system can support more detailed control models. Most of the loops have several parameters, such as the proportional, integral, and derivative (PID) constants of their controllers, and their delays. Delay means the amount of time between the command and commencement of a motion. The assumption is of control delay, not sensor delay: that is, we assume that "sensors" (visual or robot- and eye-control motor states read from their controllers) are available to the system immediately, without delay, and thus reflect the true state of the world. (Our analysis and the algorithms extend to the case that the sum of control and sensor delays is constant for any controller.)

There are five separate control systems.

1) Saccade: fast slewing of cameras to point in commanded direction. Saccades are modeled as open loop, though in primates there are "secondary" saccades that correct errors in initial saccades. The saccadic system tries to foveate the target and to match eye rotations to the target velocity so as to be tracking the target as soon as the saccade is completed. Current opinion is that the saccadic system is aware of the 3-D location of the target, not just the location of its retinal image. However, in the implementation used for the experiments (Section V), saccades operate with retinal locations and velocities, not 3-D locations or distance. The left eye is dominant in the system. The saccade aims to center the target image on the fovea of the left eye; the right eye is panned by the same amount (and, of course, tilted by the same amount for mechanical reasons). Thus the saccade maintains the current vergence angle. It is implemented as a constant-speed slewing of all three pan and tilt axes, with one of them attaining a system constant maximum velocity. The slewing continues until the target should be foveated (it may not be due to peripheral blurring or other noise), at which time the system is left with eye velocities that match the perceived target motion before the saccade. The saccadic system is characterized by its maximum velocity and its delay.

2) Smooth Pursuit: tracking a moving target. This is a "continuous" activity as opposed to the discontinuous saccadic control activity. The error here is target position in the left eye, (which should be (0,0)), and the commands are pan and tilt velocities to the left eye. The pursuit system has delay and PID control. In both the saccadic and smooth pursuit systems modeled here, there is strict (exclusive) left-eye dominance.

3) Vergence: the vergence system measures horizontal disparity between the target position in the left and right eyes, and pans the right eye to reduce it. The vergence system has delay and PID control.

4) Vestibulo-Ocular System: the VOR system is open loop in the sense that its inputs come from the head positioning system and its outputs go to the eye positioning system. Its purpose is to stabilize eyes against head motion, and its inputs are the control signals for head position (XYZ velocities, ABC angular velocities). It also uses the distance of the target, since that affects the appropriate response. The VOR should ideally be implemented by inverse kinematics, to which the current implementation (and presumably the neural one) is an approximation. Its output are commands to the pans and tilt controls to null out the apparent target motion caused by head motion. It is characterized by delay and open-loop proportional gain.

5) Platform Compensation: This system is a head control, not gaze-control system. These systems are known to interact in subtle and complex ways, but this particular reflex simply attempts to keep the eyes "centered in the head" so that the camera pans or tilts are kept within "comfortable" mechanical ranges. The "comfort function" is a nonlinear one $x/((x - x_{max})^2)$, where x is the average pan angle (to control head "yaw" movements) or the tilt angle (to control head "pitch" movements). In either case x_{max} is the mechanically imposed limit of the system. This reflex is open loop (eye position affects head position), with delay and open loop proportional gain.

The system has the capability of operating in two modes: *smooth pursuit* and *saccade*. In smooth pursuit mode, the VOR, platform compensation, pursuit, and vergence systems are left running. In saccade mode, other controls may be disabled. This allows modeling of the effects of turning off vergence, head compensation, tracking, etc., during saccades. Ultimately it seemed best only to turn off tracking during saccades, but other combinations are demonstrated in Section V.

The saccadic system shuts down the pursuit system in the sense that for the duration of the saccade (which is computed from the image distance it must move the fovea and the maximum velocity it can move), all other commands in the pipeline are overwritten, and the mode is changed to "saccade." Further commands trying to affect these instants may be ignored, depending on the (compile-time) policy desired.

B. Nonzero Delay Control

Slight amounts of delay destabilized the simulated system, as expected (see Section V). Control with delays can be stabilized by turning down gains and slowing the response of the system, but its performance then suffers. Successful control with delays incorporates some form of prediction [25]. The controller implemented in the simulation is a version of a Smith predictor [36], [37], which is the basic idea behind most modern methods.

Smith's principle is that the desired output from a controlled system with delay p is the same as that desired from the delay-free system, only delayed by the delay p. Let the delay be z^{-p}, the delay-free series controller be $C(z)$, the desired delay controller be $\tilde{C}(z)$, and the plant be $A(z)$. The delay-free system transfer function will be

$$\frac{CA}{1+CA}.$$

The delay system with its desired controller has the transfer function

$$\frac{\tilde{C}Az^{-p}}{1+\tilde{C}Az^{-p}}.$$

However Smith's principle is

$$\frac{\tilde{C}Az^{-p}}{1+\tilde{C}Az^{-p}}=\frac{CAz^{-p}}{1+CA}.$$

This quickly leads to the specification for the controller $\tilde{C}$ in terms of C, A, and z^{-p}:

$$\tilde{C}=\frac{C}{1+CA(1-z^{-p})}.$$

This simple principle has spawned a number of related controllers, often arising from each other by simple block-diagram manipulation. Fig. 1 describes the implemented system in the simulator, and is an example of Smith prediction control. The block diagram is easily derived from the Smith predictor equation, with the MODEL PLANT, MODEL WORLD, and MODEL SENSOR blocks corresponding to A. $\tilde{C}$ is represented by the block labeled CONTROL and everything below the dashed line. The CONTROL block represents all five control systems, and the DELAY block represents a vector of their five independent delays. The PLANT, WORLD, and SENSOR blocks represent the robot simulation.

C. Implementation

The main data structure used by the simulator is a pipeline of robot states (a head coordinate system with three translational and three angular velocities, two camera coordinate systems with two pan and one tilt velocity, two "images" with image (x, y) positions of the object) and control vectors (six velocity controls for the head and three for the cameras). Delayed control is implemented by inserting controls into the pipeline to take place at the appropriate future instant. Time is discretized to some level, called a *tick*, henceforth. A larger delay results in entry of the corresponding command further in the future. Control saturation can be modeled easily by dividing the commanded change between as many discrete time periods as necessary to achieve the desired effect at maximum control output. Each instant also has an entry corresponding to its mode (saccadic or pursuit). The pipeline is implemented as a ring buffer.

If the maximum delay of a controller in the system is T, the plant model has enough future robot states to reach time T into the future, updated and extended once a tick. Ideally the robot's state is predictable, since only the control commands act on it. Practically, there may be some plant noise. In the experiments reported here, the world prediction is simplified by assuming the world is static and that the robot does all the moving (navigation in a static environment). As part of the experiments, unmodeled target motion was added to test the system's response to a false target model.

A cycle of control activity involves the application of a control action for the current time, the computation of new controls using one of the control schemes described in Section V, the updating (by overwriting or addition) of the (perhaps saturated) control action in the pipeline corresponding to the correct delay, and the simulated application of all controls in the pipeline to the system to update the pipeline of simulated states. Saturated control is important since time-optimal control is often achieved by a saturated, "bang-bang" style. The explicit simulation in the predictive control system deals with saturation in a uniform manner.

V. Experiments

A. Delay-Free Control

This paper does not attempt to prove stability or performance results. Any such proofs would be misleading: the necessary data are not available, and the model of control is probably not an accurate reflection of any real system. What we desire is a convincing qualitative illustration of the effects of different styles of control interaction, and in fact, the difference between satisfactory and unsatisfactory performance should be clear in the results.

In all the simulations, the goal of the system is to put one or both of its eyes squarely on the target (at retinal position (0,0)) and keep them there. The head is always in an upright position, so pans rotate the cameras about a vertical world axis, tilts rotate the cameras about a horizontal axis. With a static head, pans induce image x motion upon a static, foveated target and tilts induce image y motion. In all the graphs of this section, the horizontal axis is time, and the vertical axis is pan and tilt error, or equivalently the image x and y position of the target. Each graph shows both left and right eye x and y errors, but often the y errors are superimposed since the tilt platform is common to both cameras. In every case there is "peripheral blur" that is modeled by adding, outside a small "fovea," uniform noise to the target (x, y) location, with standard deviation proportional to $1/d$, where d is the euclidean distance of (x, y) from the (0,0) point. The simulation does not use realistic time-constants and speeds, which instead are scaled so that interesting effects happen within a few ticks.

Fig. 2 illustrates the cumulative effect of simply superimposing control capabilities: each operates independently and their outputs are simply summed at the effectors. Delays are zero, and tracking is by position error signal. In Fig. 2(a), the left (dominant) eye pans and tilts, inducing tilt in the right eye. The right eye gets no pan signal, and its horizontal error accrues from target motion. The left eye tracks successfully until it hits mechanical stop at tick 14. In Fig. 2(b), vergence is added: both eyes hit stops at about tick 15. In Fig. 2(c), head compensation is added: this control is to keep eyes from hitting mechanical stops by turning the head in the same direction as the tracking motion. A less desirable effect is to amplify the tracking signal, overcompensating and destabilizing the tracking. In Fig. 2(d), VOR is added, which effectively compensates the head rotation with eye rotations. In Fig. 2(e), an initial saccade occurs during which vergence, VOR, and head compensation are turned off. The

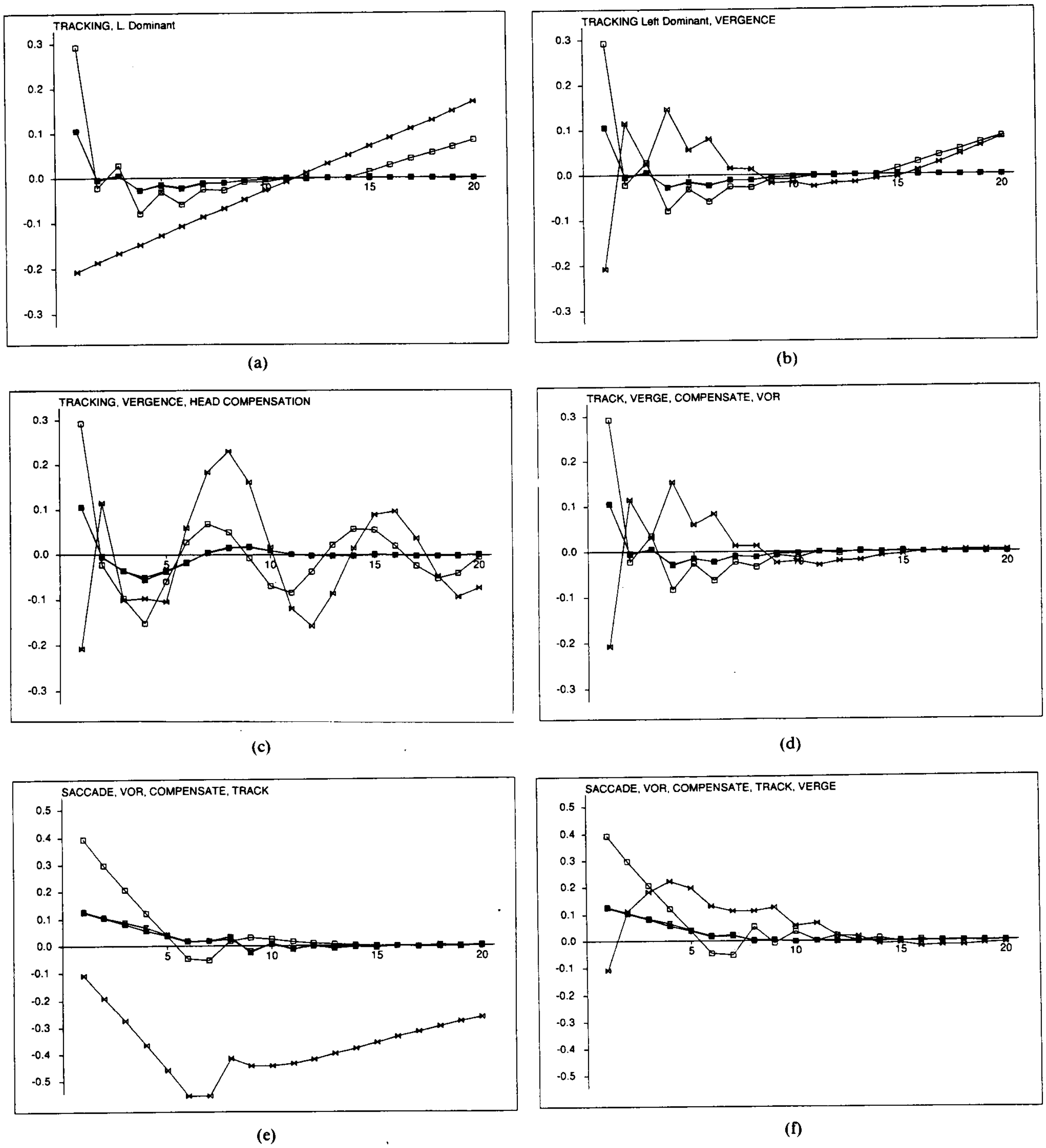


Fig. 2. Increasingly effective delay-free control from superposition of noninteracting controllers. Horizontal axis is time in ticks, vertical axis is angular tracking error in radians. Hollow square and butterfly show pan error for dominant (left) and right eye respectively. Dark square and hour glass show tilt error for left and right eyes respectively: for distant objects these errors are similar due to the common tilt platform. (a) Tracking only. (b) Add vergence. (c) Add head compensation. (d) Add VOR. (e) Add saccades. (f) Let VOR, vergence, and head compensation run during saccades.

saccade drives the left eye error more or less to zero (it is affected by the peripheral blurring effect which makes the initial location of the target image uncertain). It slews the right eye off target. When VOR, head compensation, and vergence are turned on after the saccade the first two reflexes have a transient effect. In Fig. 2(f) vergences runs during the saccade but VOR and head compensation are still inhibited until after saccade completes. This experiment seems to illustrate emergent sophisticated behavior from the independent action of several low-level behaviors.

Fig. 3 shows the effects of tracking with a velocity error signal. Here "catch-up" saccades are initiated if the target falls outside a fixed distance (here 0.1) from the fovea. Tracking exhibits a predictable steady-state position error. Position-error tracking is called for if the low-level visual routines output target position

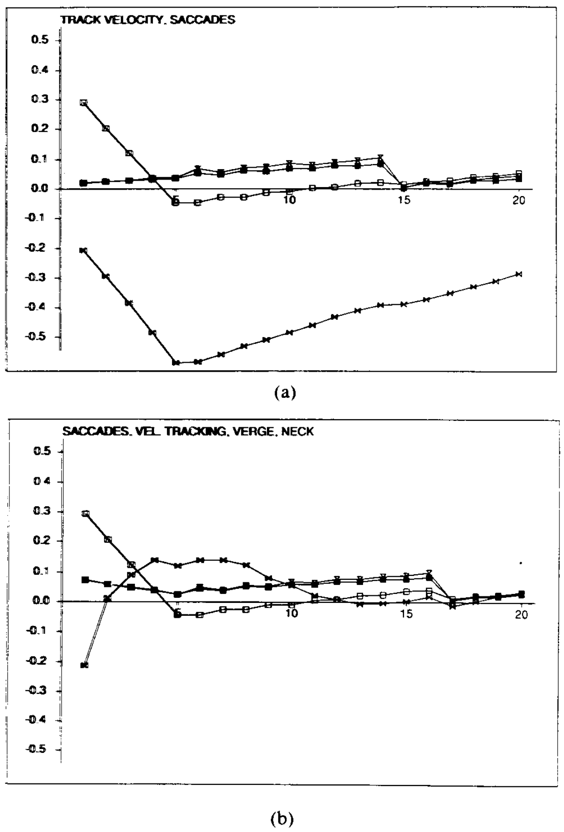


Fig. 3. Velocity-error tracking. (a) No vergence. (b) Add vergence.

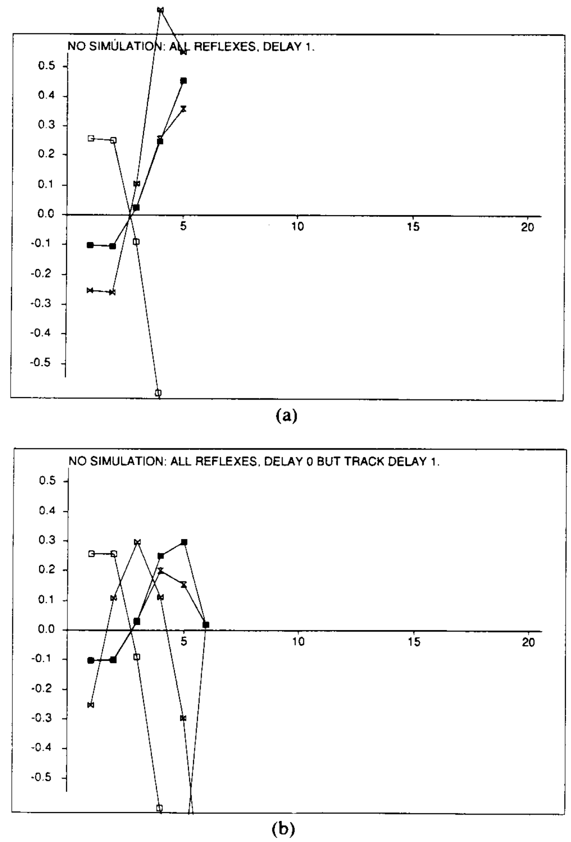


Fig. 4. The effect of delay on the no-delay controller. (a) Delay of one tick in all controls. (b) Delay of one tick in tracking only.

(as they do when calculating blob centroids), and velocity error may be more appropriate if the output tells relative displacement (as from a correlational detector, optic flow, or motion blur).

One fundamental problem with independent low-level behaviors is shown in Fig. 4. The problem, control delay, is both serious and quite familiar to control theorists and physiological modelers. The smallest delays, applied uniformly or to just one control, destabilize the system seriously. Ideally the graphs in the figure should be delayed versions of Fig. 2(d).

B. Independent Delay Control

As derived, the Smith predictor is appropriate for a single system control (or sensing) delay. In a hardware system there will be differing delays reflecting different software actions (e.g., serial line and VAL-II software for robot arm, VME-bus connection for eye motor controllers). The idea of the Smith predictor is easily extended, however. Two types of control were implemented using the Smith controller of Fig. 1. In the first, the controllers are ignorant of the delays of other controllers, and also ignorant of the sharing of output variables between controllers. Each controller knows its own delay T, and uses the following algorithm. *Look ahead time T and retrieve the predicted robot and control states for that time. Apply the control appropriate for these future states now.*

Fig. 5 shows some sample effects of this independent delay-control strategy. It should be compared with Figs. 2(d) and 4. The system is stable for certain combinations of delays, even with saccades injecting large control values, but is unstable with nonuniform delays in controls that share an output (the dominant eye).

C. Interacting Delay Control and Noise

The independent delay control algorithm is not as powerful as it could be. The short-delay controls do not look into the future as far as the long-delay controls, and therefore, they do not anticipate the effects of slower controls. This effect shows up when long- and short-delay controls affect each other's output, either directly or through the kinematic chain. The reason the verge reflex can run with different delay and not destabilize the independent delay control system is that no other control (barring saccade) affects the right camera's pan velocity, and panning is at the end of the kinematic chain. Assume each controller knows its own delay T, and the delays of all the other controllers in the set $\{S\}$ that share an output with it. Then each controller can use the following (interacting controls) algorithm. *Look ahead the maximum delay M of any controller in $\{S\}$ and retrieve the predicted robot and control states for that time. Apply the control appropriate for these future states at (possibly future) time M-T.* This algorithm successfully copes with a different delay for each control (Fig. 6(a)).

An easy implementation of this algorithm that loses some flexibility is simply to increase the delay of all controls that share an output to be the maximum delay of any of their number and apply the independent delay control algorithm. Then all controls in the set look ahead as far as their slowest member and act at the current moment. The resultant slowing of fast controls is of course suboptimal when they do not have to act in concert with slow controls.

Fig. 6 shows some experiments with interacting delay control, including stochastic disturbances in the inputs and delays. The

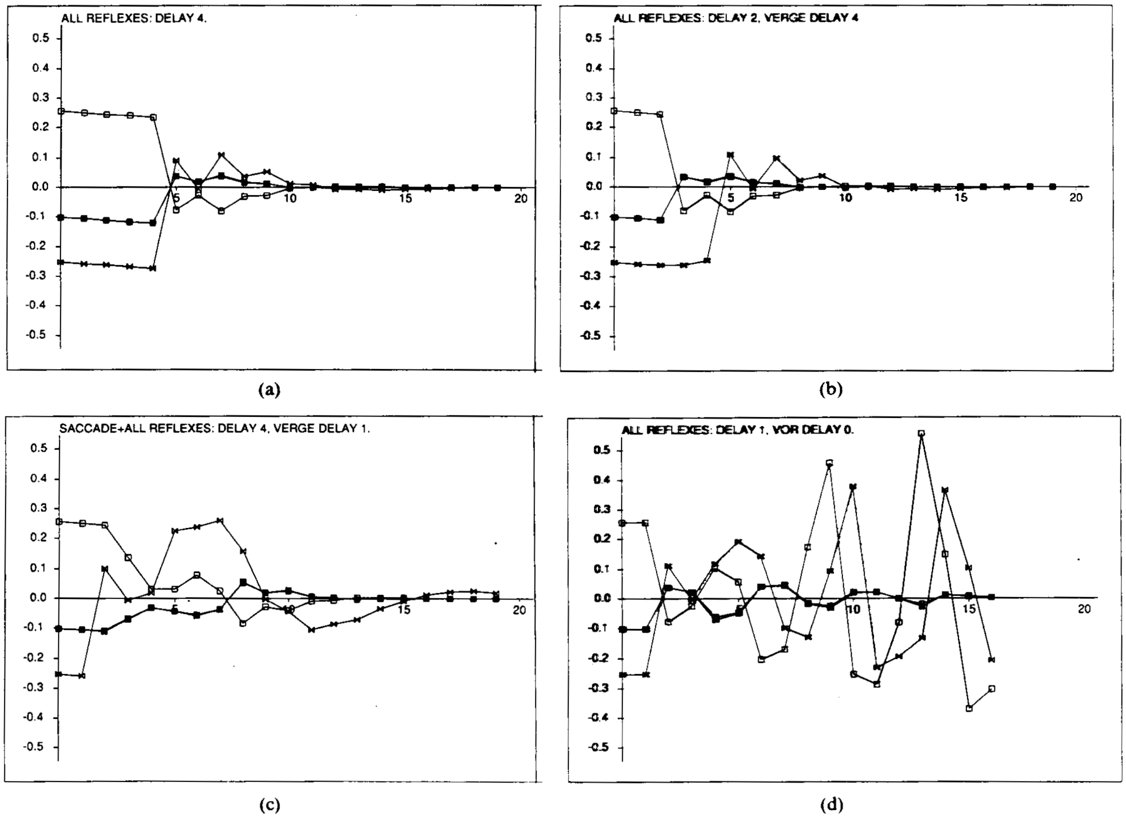


Fig. 5. (a) Independent delay control is stable with uniform controller delays. (b) Stability with only vergence control different. (c) Stability despite transients from saccades. (d) Instability if a nonvergence control, here VOR, has different delay from other nonvergence controls.

system is robust against sensor noise, or varying uncertainty in target location. In Fig. 6(a), the interacting control algorithm deals successfully with a mixed set of delays. Here the longest nonvergence delay is three ticks, and the resultant behavior is that of a system whose nonvergence controls have a uniform delay of that amount. In Fig. 6(b), sensor noise (uniformly distributed disturbance of the target (x, y) location in each eye with $\sigma = 0.02$ in each dimension) does not affect stability, but causes excursions larger than its σ through the interaction of tracking and verging.

It is well known that the sensitivity of control to temporal variation varies as the derivative of the control signal. This result is illustrated in Fig. 6(c) and (d), which have identical parameters but different results. In both, with probability 0.1 a control signal is delivered one tick early, and with probability 0.25 it is delivered one tick late. In Fig. 6(c) the system is on the verge of instability. In Fig. 6(d), more disturbances happen to occur early in the sequence when outputs are changing rapidly, destabilizing the system.

In Fig. 6(e), the previous sensor noise is added to the system along with the previous stochastic delays: the system is stable. In Fig. 6(f) there is no noise (other than peripheral blurring), but the target model is in error. The target is moving approximately perpendicular to the robot's motion instead of remaining static. The error periodicity of 10 ticks is interesting. In Fig. 6(g) the target is moving faster, and toward the robot. As it gets close the controls cannot respond fast enough and the system destabilizes. The problem is inaccurate world modeling, and motivates work to create and maintain a dynamic model of the object being tracked.

VI. Conclusion

Gaze control is a much studied complex sensorimotor ability. In gaze control, several simple "reflexes" or "behaviors" cooperate to achieve effects such as gaze shifts, object tracking, and gaze stabilization. Attempting to implement (in simulation) some simple aspects of gaze control led to several conclusions.

The behaviors acted like a multirate, multiinput, multioutput, time-delayed, saturated control system. Explicit coordination between behaviors was needed to let them cooperate effectively (stably, accurately) in the presence of time delays and control interactions. The coordination in this case is through a shared data structure that predicts the future state of the active agent. A behavior is assumed to know the maximum time delay of any behavior with which it shares an output. The resulting control is a form of the Smith predictor, and seems to offer one general solution for this type of problem.

The work so far has uncovered areas for improvement, which are underway and will be reported elsewhere.

1) All controls operate from retinal coordinates. Predictions of object position and velocity in head or laboratory coordinates are needed to predict retinal images. Head rotations, pans, and tilts all induce camera origin translations due to the geometry of the head, and nonretinal representations are more robust (as when the object tem-

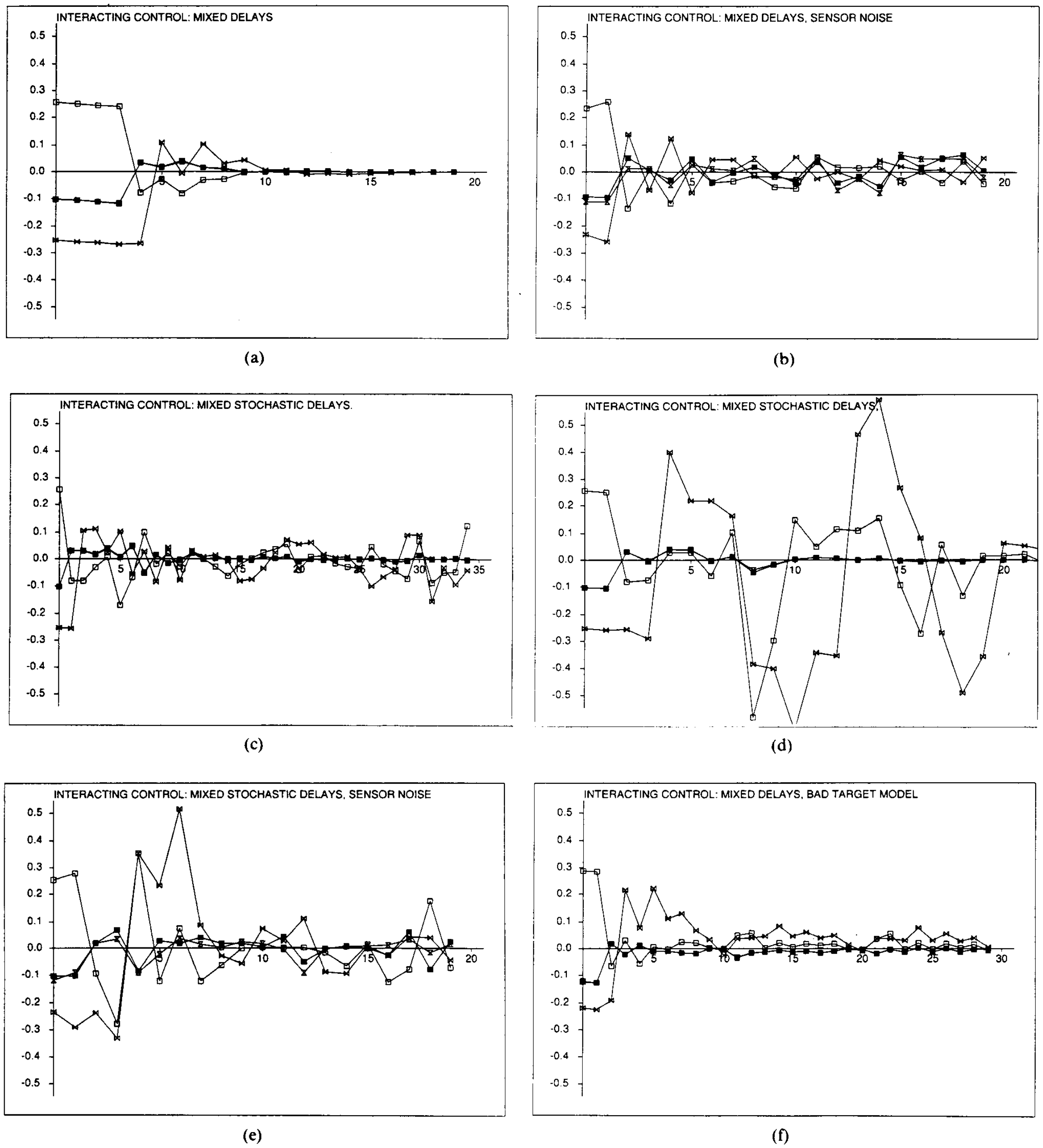


Fig. 6. Interacting delay control. (a) Stability with a mixed set of delays. (b) Stability with sensor noise. (c), (d) Illustrating sensitivity to stochastic delays. (e) Sensor noise and stochastic delays. (f), (g) Inaccurate target model.

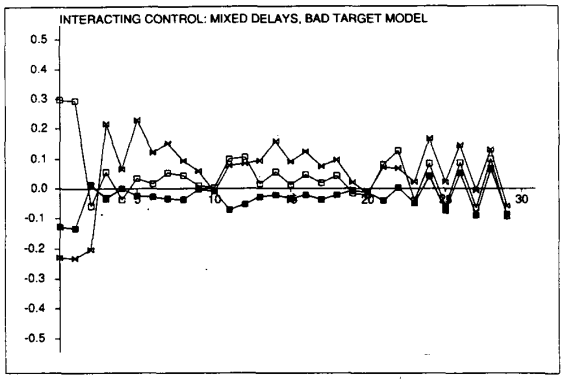
porarily is lost). There is evidence that primate systems use target depth as well as retinal position in gaze control [10].

2) There is no capability for estimating the state of objects moving in LAB (relative motion was produced with a static object and observer motion.) A pipeline of object state descriptions should be maintained to predict object state from observations. We plan to integrate Kalman filtering techniques [13], [7] to perform estimation of the target's state. Also, we may explore estimation techniques [9], [18], [20] instead of simulation techniques to predict the state of the plant. Adaptive techniques can be used both to select predictive models and to tune the expected delays.

3) The head compensation reflex is the only head control. The system should be provided controls for fast and tracking head motions.

4) The eye control algorithm is unsophisticated, and there was no significant head and eye cooperation for quick gaze shifts. Fast gaze-shift algorithms involving both head and eyes will be investigated.

5) The two modes of operation (pursuit and saccadic) are simplistically assumed to correspond to inflexible combi-



(g)

Fig. 6. *Continued*

nations of lower level capabilities. All controls should be activated and deactivated independently, and their smooth cooperation thus becomes another research issue.

Although the simulation captures many relevant aspects of the Rochester robot; it is not a quantitative tool but a testbed for styles of interaction. The simulator's exterior world and image-processing model is simple, consisting of a single point whose image is instantaneously and reliably (if noisily) found. To some extent this is realistic, since it reflects the capability of certain frame-rate feature detection algorithms [12], but it ignores the existence of more sophisticated operations or those with longer time-constants. Current work is aimed at quantifying the behavior of the Rochester robot and improving the speed of certain basic communications and vision capabilities. Sensitivity analysis will be undertaken to quantify the effects of various disturbances, especially the problem of unpredictable delays.

Since kinematic simulation forms an integral part of the control algorithms, parts of the simulator will probably be applied in control of the physical system. Simulation will probably not be used to justify system performance, however. As the control and visual environment grow more complex the simulations become slow, costly, and unconvincing. The advent of cheap real-time hardware makes it increasingly practical to replace simulation demonstrations with real-world experiments.

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