A PRODUCTION SYSTEM MODEL OF CAPTURING REACTIVE MOVING TARGETS

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ABSTRACT

Subjects manipulated a control stick to position a cursor over a moving target that reacted with a computer-generated escape strategy. The cursor movements were described at two levels of abstraction. At the upper level, a production system described transitions among four modes of activity: rapid acquisition, close following, a predictive mode, and herding. Within each mode, differential equations described trajectory generating mechanisms. A simulation of this two-level model captures the targets in a manner resembling the episodic time histories of human subjects.

INTRODUCTION

There seems to be a growing consensus that complex motor behavior must be described at multiple levels of abstraction. This notion is at least as old as Bryan and Harter's (1899) work on telegraph operators. More recently Rasmussen (1983) has discussed skill-based, rule-based and knowledge-based behaviors. The present experiment used two levels of abstraction to describe the way people capture a moving target. The more abstract level of description consisted of a production system which exhibited discrete transitions among modes of capture behavior. The more detailed level of description consisted of the trajectory generating mechanisms that were active within each mode. The simulated time-histories of this two level model contained sequences of episodes corresponding to the activation of different tracking modes. The time histories of human subjects were similarly episodic.

The episodic nature of manual tracking was emphasized by Craik (1947) in his characterization of the human operator as an intermittent correction servo. A number of subsequent sampled-data models exemplified this approach (e.g., Lemay and Westcott, 1962; Bekey, 1962; see Pew, 1970 for additional discussion of this issue). In contrast, smooth continuous descriptions of tracking such as the McRuer Crossover Model (McRuer and Jex, 1968) and continuous optimal control models (e.g., Kleinman, Baron, and Levison, 1971) have not emphasized episodic aspects of performance.

A somewhat intermediate class of models has described episodic aspects of manual tracking as switching among a set of control modes, some or all of which were smoothly continuous. For example, Costello (1968), Phatak and Bekey (1969), and Burnham and Bekey (1976) partitioned the error phase plane into several regions, and associated a different tracking mode with each region. The episodes in these latter models were thus event-driven, rather than time-driven as in the sampled-data models. The simulation used in the present study was a generalization of this event-driven approach, in which the events that triggered the beginnings of episodes included aspects of the target and cursor movement in addition to error and error rate.

METHOD

Four undergraduate students served as subjects for ten 45-minute sessions. Subjects sat approximately 50 cm away from a 10-cm wide oscilloscope display on which they saw a target and a cursor. The target consisted of two vertical lines separated by 2 mm, and the cursor was a single dot. Both target and cursor moved only in the horizontal dimension. At the beginning of a trial the cursor was centered, and the target randomly appeared 2 cm to the right or left of center. The subjects' task was to manipulate an isometric control stick (gain = .35 kg per 1° of visual angle) so as to hold the cursor dot between the two target lines for an uninterrupted period of 400 ms. When this criterion was achieved, the target was considered "captured," and it disappeared from the display. If the target was not captured within 15 seconds, or if the target exceeded the display boundaries of 5 cm to the right and left of center, the target was considered to have "escaped," and it also disappeared from the display. The subjects' task was to capture the target as quickly as possible.

The target reacted to the movement of the cursor with an escape strategy represented in Figure 1. A nonlinearity plus an integrator made the target move away from the cursor with a velocity that increased as the cursor came closer (a "panic" function). The resulting velocity was then filtered through a second-order underdamped system that made the target movement oscillatory. There was a 15 cm/sec saturation on velocity and a $15\omega_n$ cm/sec^2 saturation on accelaration in this filter that is not represented in Figure 1. ω_n is the undamped natural frequency of the filter. The purpose of the filter was to have the target make evasive side-to-side movements analogous to the juking maneuvers performed by footbal players attempting to elude a tackler.

ω_n was set at either 3 or 5 rad/s, and the per unit critical damping, ζ, was set at either 0 or .25 . A factorial crossing of these values produced four targets of varying degrees of evasiveness.

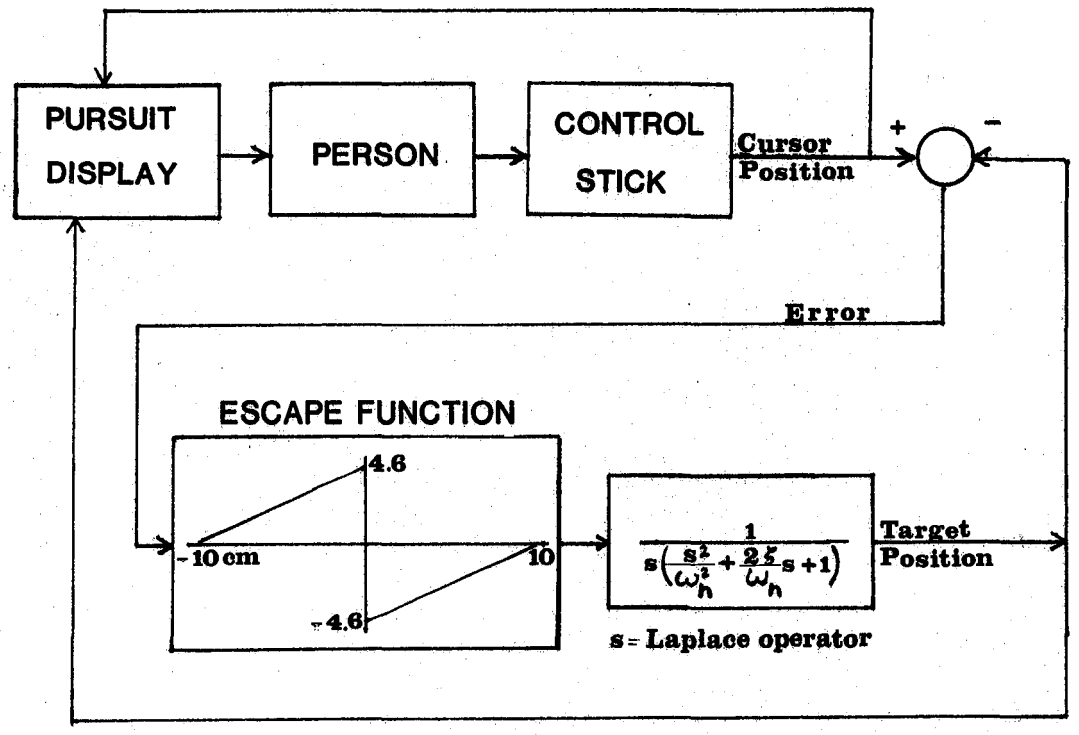

Figure 1 - Escape strategy for reactive targets.

For each of the four targets, subjects received two practice trials followed by two 20-trial blocks. Each session thus consisted of 160 data trials, 40 trials for each target. The order of presentation of targets was randomized within a session; however, subjects were informed as to which target they would receive at the beginning of each block. Subjects were instructed to capture the targets as quickly as possible, and were given feedback after each block as to the sum of their capture times over the twenty trials. Whenever the target escaped, a capture time of 15 s was recorded for that trial. There was thus a strong penalty for an escape. Subjects were also given daily feedback on their total capture time across all 160 trials, and a bonus of $5.00 was offered to the subject with the lowest total capture times for Sessions 9 and 10.

RESULTS

State Definitions

Mean capture times on Sessions 9 and 10 ranged from 3.2 s for Subject 1 to 6.1 s for Subject 4. For all four subjects, mean capture times increased

monotonically across targets in the following order: (ω_n = 3 rad/s, ζ= .25), shortest capture time; (ω_n = 3 rad/s, ζ = 0); (ω_n = 5 rad/s, ζ = .25); (ω_n = 5 rad/s, ζ = 0), longest capture time. A single trial for Subject 1 capturing the most difficult target is shown in Figure 2. Qualitatively, this time history appears to contain a sequence of short episodes of very different types of pursuit behavior. After a reaction time interval of approximately 300 ms (RT segment, Figure 2), the cursor moves very rapidly toward the target to reduce the initial large distance from the target (first A segment, Figure 2). Once the cursor nears the target, the cursor begins to follow the target closely and mimic the target trajectory (first F segment, Figure 2). After several changes of direction, the discrepancy between the target and cursor builds up, and the cursor no longer mimics the target trajectory (segment P, Figure 2). Rather, the cursor moves much more slowly than the target, coming close to the target only at its upper turnaround points. The cursor then begins to follow the target closely again (second F segment, Figure 2) until the target approaches the 5-cm escape boundary. The cursor then exhibits a quick pulse that has the effect of reversing the target movement (second A segment, Figure 2). Finally, the cursor again begins to follow the target closely, and the target is captured (third F segment, Figure 2).

The boundaries of the episodes indicated in Figure 2 were determined by a computer program that was basically looking for three patterns:

1. A - "fast acquisition" Cursor velocity is much greater than target velocity.
2. F - "close following" Cursor velocity is approximately equal to target velocity.
3. P - "predictive mode" Cursor velocity is much less than target velocity.

The distinction between a fast acquisition as in the first A segment in Figure 2 and close following is similar to the two modes in Costello's (1968) surge model. Large errors are corrected proportionately more rapidly than small errors. The second A segment in Figure 2 keeps the target in bounds rather than reducing a large discrepancy. This type of response might better be labelled "herding". More will be made of this distinction later in this paper. The predictive mode is also quite different from close following. The subject seems to know that the target is eventually going to turn around and oscillate back toward the cursor. This behavior seems to involve more long-range prediction of target behavior.

The three patterns, A, F, and P were more quantitatively defined as a trichotomy on the ratio of target velocity to cursor velocity. However, such a definition is based on very local movement characteristics rather than more global pattern recognition, and it ran into problems when the target paused or reversed direction, or when cursor and target had approximately equal velocities of opposite sign. The computerized pattern recognition scheme was therefore supplemented with additional

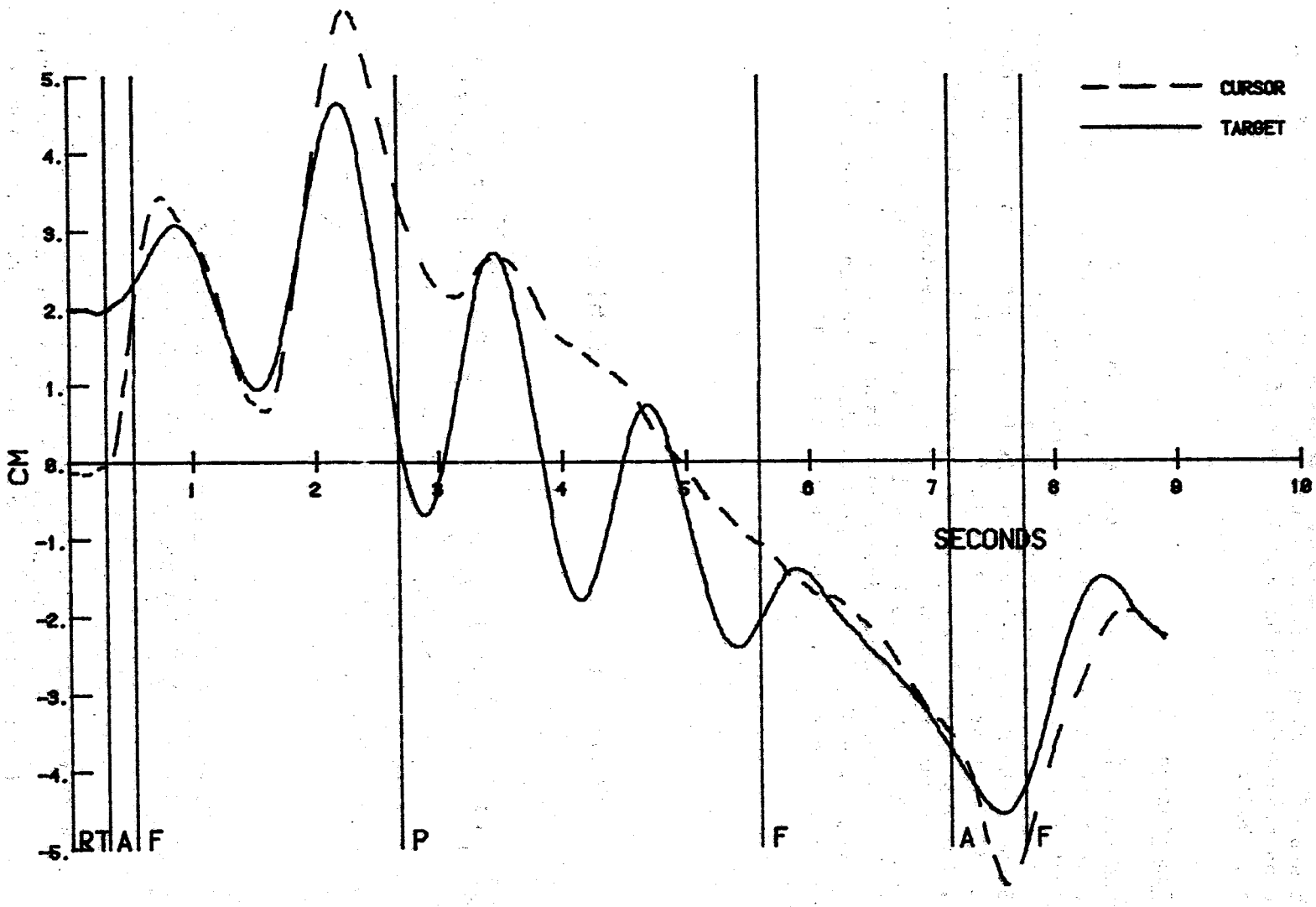

Figure 2. Time history of Subject 1 capturing the most difficult target.

local tests of error magnitude and cursor velocity, as well as more global tests of tracking mode continuity. The details of these pattern recognition procedures are beyond the scope of the present summary (see Plamondon, 1982).

Markov Descriptions

Using the three state definitions A, F, and P, a computer program segmented the continuous time history of each of the trials into a sequence of discrete states. For each target, the pattern of state transitions across trials was represented as a first order Markov process. Figure 3 shows the Markov representations for Subjects 1 and 4 capturing the most difficult of the four targets (ω_n = 5 rad/s, ζ = 0). For each subject, the representation is based on a total of 80 trials from Sessions 9 and 10. The number in each circle is the mean duration of that state in seconds. The number on each arrow between states represents the probability of going to a particular new state given that a transition occurred from the old state. Transitions which occurred on less than five percent of the trials are not shown in the figure.

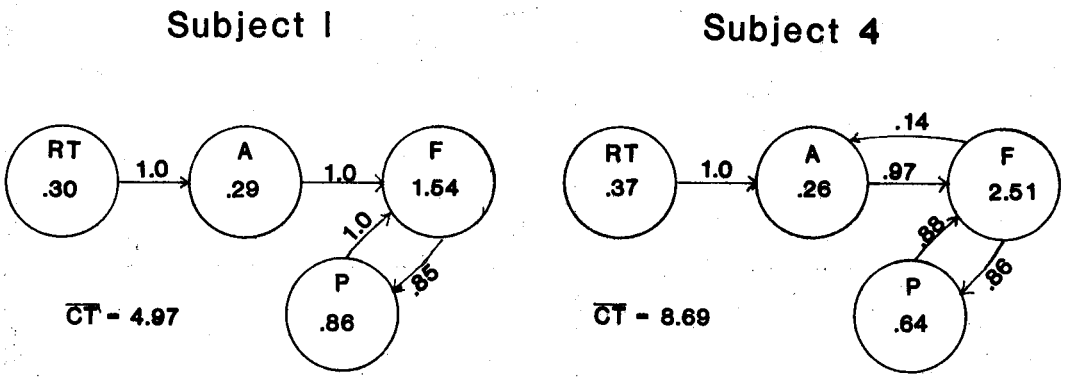

Figure 3 - Markov representations of subjects' strategies in capturing the most difficult target.

At this very abstract level of representation, the subjects' strategies for capture look quite similar. After an initial acquisition mode, close following occurred. Transitions to the predictive mode and

a return to close following might occur subsequently. Subject 4 occasionally transitioned from close following to the acquisition mode, and the mean duration of Subject 4's following mode was about 1 second longer than for Subject 1. On the other hand, mean capture time for Subject 4 (8.69 s) was almost four seconds longer than the mean capture time for Subject 1 (4.97 s). Subject 4 captured only 47 of 80 targets, while Subject 1 captured 76 out of 80. Given these large differences in overall performance, it is somewhat surprising that the Markov diagrams are so similar.

One aspect of performance missing from these diagrams is the states of the cursor and target when the mode transitions occurred. Phase plane diagrams of cursor, target, and error revealed striking individual differences between Subjects 1 and 4 when transitioning into the P mode. Subject 1 transitioned into the P mode primarily when the error was increasing (a well defined linear locus in the first and third quadrants of the error phase plane), and target velocity was greater than 5 cm/s. Subject 4 had a more diffuse spread of points in the first and third quadrants of the error phase plane, and no well defined pattern in the target phase plane. Cursor velocity was less than 1 cm/s for 28% of Subject 4's entries into the P mode, indicating that some of the activity classified as "predictive" may have simply been pausing. In contrast, Subject 1 tended to generate ramp-like cursor movements during the P mode, and cursor velocity was never less than 1 cm/s at entry to the P mode.

Production System Model

Based on the previous analysis, a two-level model of capture performance was constructed. The upper level was a production system model that generated transitions among four different modes of activity (Table 1). The fourth mode arose from treating herding and the reduction of the initial large tracking error at the beginning of a trial as two separate A modes. Each mode has an associated goal, and the productions are ordered to reflect the urgency of these goals. Preventing an escape (herding) has the highest priority, and reducing large oscillations via the predictive mode has second priority. Staying close to the target to achieve capture (close following) cannot be successful if the target is about to escape or if it is wildly oscillating. This goal was therefore given third priority. The fourth goal, reducing the large initial error, applies only at the beginning of trials.

The trigger conditions for entering the P and F modes were based on the phase plane patterns for Subject 1. Very few herding responses were detected by the computer pattern recognition scheme previously described, so the entry conditions for the herding maneuver are not derived from subjects' data.

Once begun, a mode of tracking continues until it produces states of target and cursor that match the entry condition for a different mode to begin. If more than one entry condition is satisfied simultaneously,

Table 1 - Annotated Production System

Goal	Triggering Condition	Movement Trajectory
1. Keep target away from boundary	$\lvert T \rvert > 3.5$ cm and $\lvert T + .25\,\dot{T} \rvert > 5.0$ cm and $\lvert E \rvert < .65$ cm	Herding response (A_2) Rapid, preprogrammed pulse
2. Reduce large oscillations	$\lvert \dot{T} \rvert > 5$ cm/sec and $\lvert \dot{T} \rvert > \lvert \dot{C} \rvert$ and $\lvert E \rvert$ increasing and $\lvert E \rvert > .3$ cm	Predictive response (P) Ramp response to closest predicted turn-around point by damped sinusoidal schema $\hat{T} = T_o + e^{-bt}\, r \sin(\omega t + \theta)$ and closed-loop error nulling (low gain) and strong velocity limiting
3. Stay very close to target to achieve capture ($\lvert E \rvert < .10$ cm for .4 sec)	$\lvert E \rvert < .65$ cm	Close following response (F) Position cursor at short-range damped sinusoidal extrapolation of target position and closed-loop error nulling (high gain) and slight velocity limiting

Table 1 - continued

Goal	Triggering Condition	Movement Trajectory
4. Reduce initial large error	Initial conditions	Fast acquisition response (A_1) Rapid, preprogrammed step

T = target C = cursor E = error = T - C

the highest priority condition takes precedence. This system is thus deterministic. The probabilistic nature of mode transitions in the Markov description is resolved by the explicit entry conditions in the production system.

The second level of the overall model is the trajectory generating mechanism within each tracking mode. The initial acquisition response, A_1, was generated from the step response of a second-order underdamped system. Low damping and a high undamped natural frequency generated a fast rise time. The damping was then increased and the undamped natural frequency was decreased to shape the overshoot aspect of the response. This preprogrammed response was protected from interruption by other tracking modes for 450 ms. The herding maneuver, A_2, was similarly generated from the pulse response of a second-order system with high undamped natural frequency and low damping. This preprogrammed response was protected from interruption for 400 ms.

The trajectories for the predictive or P mode were generated from a combination of three mechanimsm: a predictive element, a closed-loop error nulling element, and a velocity limiter. The predictive element used a damped sinusoidal model of target motion. Target position and target velocity 150 ms and 300 ms into the past were used to estimate continuously the target model parameters for amplitude, frequency, phase, and offset. The damping constant was fixed as apriori knowledge of the target. In the predictive mode the cursor does not keep up with the target. The subject anticipates that the fleeing target is going to turn around and start coming back, and then turn around again in an oscillatory manner. The predictive element therefore continuously predicted the position and time of the nearer turnaround, and generated a cursor velocity sufficient to intercept the target at turnaround (see the P segment in Figure 2). This predictive behavior was combined with a closed-loop error nulling element in the form of a simplified McRuer Crossover Model with low gain and 150 ms time delay. A velocity limiter approximated neuromuscular smoothing.

The close following or F mode used the same three elements as the predictive mode, but modified their interaction. The predictive element used the damped sinusoidal model to predict present target position based on target position and target velocity 150 ms and 300 ms into the past. The change in cursor position necessary to match this predicted target position was weighted by a factor reflecting how accurately the damped sinusoidal model had recently predicted past target position. This predictive element was combined with a high gain McRuer Crossover Model and a less severe velocity limiter than was used in P mode.

The production system is a deterministic model. Given the constant initial condition at the beginnings of trials, only a single time history would be generated for each of the four targets. Subject data, however, exhibited considerable trial to trial variability even after ten days of practice. To introduce trial to trial variability into the production system, the initial acquisition response was stochastically varied as

well as a 200 ms exponential blending function that was implemented to avoid transients when mode switching occurred. Any of the other tracking modes could also have been varied. However, the present stochastic variations were sufficient to generate an interesting variety of time histories. Three sample time histories of the model capturing the most difficult target (ω_n = 5 rad/s, ζ = 0) are shown in Figure 4.

The performance of this multi-level model has to be judged at multiple levels of detail. At the grossest level, one can simply count how often it captures targets. The model captured the most difficult target about sixty percent of the time. This level is comparable to Subject 4 (59%), but not as good as Subject 1 (95%) on Sessions 9 and 10. A slightly more detailed measure of model performance is the mode transitions it exhibits. Like Subjects 1 and 4, the model captured the most difficult target by primarily transitioning between the P and F modes. At still a lower level of detail one can compare the trajectory shapes in the different tracking modes with those exhibited by the subjects. At least qualitatively, there is strong similarity. Much work remains to be done in more formally evaluating this production system model. However, even this cursory evaluation does lend additional credence to the multi-level description of target capture behavior.

DISCUSSION

The present study has demonstrated the usefulness of combining production systems and trajectory generating mechanisms to describe the episodic nature of target capture behavior. The present authors believe these different levels of describing behavior are examples of what Rasmussen (1983) has referred to as rule-based and skill-based behaviors. In more complex environmental situations a third level of organization corresponding to problem-solving aspects of knowledge-based manipulations might be added to the present model.

The decomposition of behavior provided by the definitions of different tracking modes proved useful in developing a simulation to match human performance. An alternative would have been to work at only one level of abstraction, and attempt to represent all of the varied aspects of the target capture behavior in a single linear or non-linear differential equation. This approach probably would have been considerably more difficult given the nature of the time histories exemplified by Figure 2.

The present simulation has also demonstrated the usefulness of a simplified predictive element for successfully capturing a higher order non-linear target. Although the form of the simplified target model (a damped sinusoid) was not uniquely identified from the subjects' time histories, earlier versions of the simulation suggested that some kind of predictive mechanism was essential for achieving the tracking

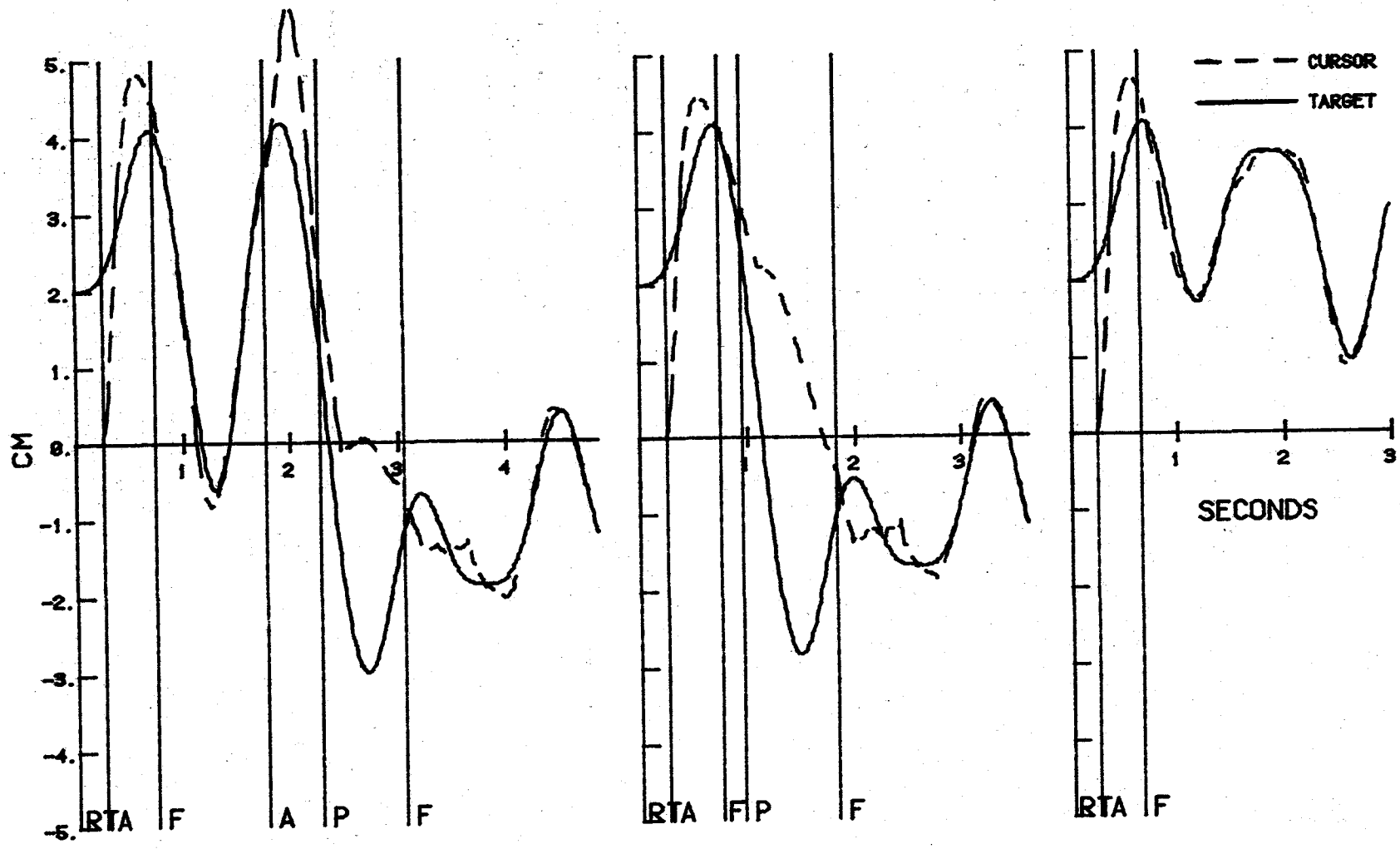

Figure 4 - Time histories of the production system model capturing the most difficult target.

accuracy required in this very demanding task. Closed-loop error nulling did not appear to be sufficient. On the other hand, complete veridical knowledge of the target dynamics was not necessary for capture. The damped sinusoidal predictive element in the P and F modes did not explicitly represent the nonlinear velocity generating escape mechanism that preceded the oscillatory filter, nor was the time history of past tracking error modeled as an input to the damped sinusoidal approximation. The usefulness of approximate prediction has also been noted by other investigators including Kelley (1962), Murril (1967), and Herzog (1968). Additional work on incorporating more global pattern recognition capability might improve the present model without resorting to full veridical knowledge of the target.

The close following (F) and predictive (P) tracking modes utilized the same basic elements of damped-sinusoidal prediction, closed-loop error nulling, and velocity limiting, but the two modes differed in the way these elements interacted (Table 1). This recombination of the same basic elements captures the spirit of what Greene (1972), Turvey (1977), Gallistel (1980) and others have termed coordination. Although the present production system model has this property, there may be other ways of representing the trajectory generating mechanisms for these two modes. The present authors do not claim that the present representation is unique.

The tracking modes used in the present production system model appear to be closely related to distinct styles of tracking noted by previous investigators. For example, Costello (1968) postulated a two-mode model for nulling large and small errors that is similar to the distinction between the fast acquisition (A_1) and close following (F) modes in the present study. The subjects' behavior in the predictive (P) mode is somewhat analogous to crossover regression (McRuer and Jex, 1968) in which subjects do not attempt to follow high frequency characteristics of the input signal. Subjects' ability to predict sinusoidal patterns in manual control tasks is also well documented (Magdaleno, Jex, and Johnson, 1970; Pew, 1974). Parallels such as these increase the credibility of the present mode definitions. Nevertheless, considerably more work is necessary to establish their behavioral independence as distinct modes of tracking. What is necessary is to find independent variables that can alter each mode individually without altering the other modes. For example, Subject 1 only used the P mode to any appreciable degree for the most difficult target. If the other modes were not altered in structurally significant ways by this manipulation of ω_n and ζ, one would have greater confidence that the P mode was behaviorally independent from the other tracking modes. Similarly, the addition of high frequency noise to the target might affect the close following (F) mode without significantly altering the fast acquisition and predictive modes. Much more work needs to be done on this important issue.

In summary, the present work has argued for the usefulness of combining production systems and differential equation descriptions of episodic target capture behavior. In more complex tasks involving both supervisory and active control, production systems may in turn be controlled by still more abstract levels of behavioral organization. By explicitly representing multiple levels of organization of tracking behavior as in the present study, it may be easier to incorporate tracking into more general behavioral models involving problem solving and decision making. The authors hope that the present effort will contribute toward the development of behavioral models at multiple levels of abstraction.

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