A MODEL-AIDED TRACKING CONCEPT FOR RANGE SENSOR SLAVING

Donald R. Vander Stoep, Ph.D.
Consultant
Ball Systems Engineering Division
San Diego, California 92121
(619)457-5550

1.0 INTRODUCTION

Sensor slaying consists of pointing a secondary (slave) sensor to a target vehicle, coordinates of which are defined by measurements from a primary (master) sensor or set of master sensors. For typical range applications, the secondary sensor does not possess an autonomous tracking capability; thus, pointing commands for the secondary sensors must be derived from an external source, i.e., the primary sensor or system. A common example of a range slaving system consists of an optical sensor (e.g., a cine- of video theodolite) slaved to a tracking radar. In this instance, radar measurements (range, azimuth, elevation) are typically converted into a cartesian set (x, y, z), followed by the computation of the azimuth and elevation angles from the theodolite site to the designated point. These angles define commands for theodolite pointing. Additional examples include the following:

- pointing of an RF emitter (possessing no autonomous tracking capability),
- pointing an optical instrument in conditions where visual target acquisition is extremely difficult due to small target size or distance,
- secondary sensor located within a range hazard area which cannot be occupied by human operators.

Potential enhancements to this process include filtering of primary sensor data, compensation for time delays in processing and data transmission, and the use of multiple primary sensors (e.g., multiple radars) to point one or more secondary sensors.

Problem areas associated with sensor slaving are frequently encountered. One such problem is pointing accuracy. Many test missions require high-quality photo documentation, which imposes narrow field-of-view, high magnification lenses, and stringent pointing accuracy requirements. A similar problem is encountered when pointing a narrow beam RF emitter. Accuracy problems are aggravated by target dynamics. A slaving system which works properly for benign targets (e.g., a non-accelerating low-speed aircraft) may fail for a highly accelerating target vehicle. An additional problem arises for low-altitude targets when the primary sensor(s) is radar, as radar performance is seriously degraded with elevation angles below 3 degrees due to the multipath phenomenon.

This paper describes a sophisticated approach to sensor slaving which minimizes the aforementioned problems. This technique, called “model-aided tracking”, embodies the following concepts:

- use of a Kalman filter (or other optimal estimator) to process measurements from single or multiple primary sensors,
- inclusion of a mathematical model of the tracked vehicle’s trajectory within the optimal estimator,
- generation of a continuous estimate of target velocity within the Kalman filter, and use of this velocity estimate to compensate for data transmission and computational delays,
- provision for real-time manual corrections, where real-time imaging of the target is available from the slave tracking mount.

This paper presents simulation results which demonstrate the performance of the model-aided tracker for test missions which pose difficulty for conventional slaving systems due to stringent accuracy requirements, target dynamics, target size, multipath, etc.

2.0 MODEL-AIDED TRACKER CONCEPT

The basic model-aided tracker is illustrated in Figure 1. The heart of the system is the optimal filter processor, which processes primary sensor measurements, producing target position and velocity estimates. These estimates are then transformed into pointing commands for the slave mount. The primary measurements can come from a single source, as indicated in Figure 1, or from any combination of TSPI sensors such as radar, laser tracker, multilateration, or GPS. Embedded within the Kalman filter is a mathematical model, or simulation, of the target’s trajectory. This model takes the form of differential equations, included within the filter structure, or a pre-computed nominal trajectory. After each measurement, the filter adjusts the model’s position and velocity based on the most current measurement information. This permits the filter to effectively deal with any mismatch between the predetermined mathematical model and the actual vehicle trajectory. The interaction of the measurements and the model within the filter are illustrated in Figure 2.

In order to establish synchronization between the filter model and the test vehicle trajectory, a timing signal must be obtained from the test vehicle. In most cases, this signal would be obtained from telemetry, sent from a weapon or a launch vehicle. The Signal could also be obtained from a ground sensor and relayed via ground communications.

An important feature of the model-aided tracker is the compensation for timing delays in the filter processor and data transmission systems. As the optimal filter will produce a real-time velocity estimate, this velocity estimate, together with the known time delay, can be used to compensate the vehicle position estimate for known time delays.

An optional feature for the model-aided tracker is a manual input. If the slave mount can be equipped with a TV camera, then the video image can be displayed in real time. The operator can detect the position of the target within the TV field-of-view, and send adjustment commands to the processor, as indicated in Figure 1. The target centroid generally drifts from the center of the field-of-view, due to biases in primary sensors or errors in the target trajectory model.

Many test missions require deployment of the slave sensor on a ship or aircraft (e.g., tests at very high altitude, or at sea locations). The model-aided tracker can be extended to such missions, as illustrated in Figure 3. In this instance, the test item and the mobile platform must both be tracked in order to generate pointing commands for the slave sensor. In addition, the mobile platform must provide attitude information to the model-aided tracker. For most applications, attitude data could be obtained from an inertial navigation system.

3.0 PERFORMANCE OF MODEL-AIDED TRACKER

Ball Systems Engineering Division has performed simulations of model-aided tracking for two test missions requiring high-quality photo documentation of the test vehicle. Simulated primary sensor measurements were used, where realistic sensor errors were included in the simulated measurements. Measurements were then processed with prototype versions of the model-aided tracker which included six-degree-of-freedom vehicle trajectory models. Simulation examples are given below.

3.1 Submunition Tracking

The purpose of this study was to establish the feasibility of the model-aided tracker for in this test was to collect high-quality photo-imagery of the test vehicle, requiring a long focal length, narrow field-of-view lens, and introducing a difficult pointing requirement for the slaving system. Visual acquisition of the submunition target by the cinetheodolite operator would be impossible, due to the small target size. The first case examined illustrates the difficulties encountered when using any primary sensor data for slaving. Figure 4 depicts the motion of the target centroid as viewed by the slave sensor, when slaving information is based solely on outputs of the radar. The horizontal lines in Figure 4 define the azimuthal field-of-view of the cinetheodolite. Similar behavior was seen in the elevation components. The worsening slaving performance with time is due to the increasing range from the tracking radar to the target. For this scenario, radar-derived slaving information is unsuitable.

Figure 5 illustrates slaving performance achievable utilizing only the simulation model of the vehicle trajectory. Use of the simulation model eliminates the noisy characteristic introduced by the radar. However, because the model is imperfect (for example, due to imperfect aerodynamic parameters or atmospheric parameters) pointing based solely on the math model is also unsatisfactory.

Figure 5 demonstrates the improvements achieved when the radar data and the model are combined in an optimal estimator. The model served as a low-pass filter on the noisy radar data, while the radar information reduced errors introduced by model inaccuracies. However, the target center did not remain within the cinetheodolite field-of-view. The desired result was obtained with manual intervention, illustrated in Figure 6. This result utilized two discrete operator corrections, which could be implemented via a joystick or a keyboard. This manual intervention would not require any significant degree of operator training or skill, as the migration of the target position relative to the sensor boresight occurs slowly. These examples confirm the difficulty of obtaining optical photo-documentation with conventional slaving, and illustrate the technical solution to this problem available with the model-aided tracker.

3.2 Ballistic Missile Trajectory

The test vehicle for this example is a ballistic munition in a near-vertical downward trajectory, experiencing high acceleration due to the deployment of a parachute. This test, like that of the previous example, required high-quality photo-documentation of the test vehicle, undergoing severe accelerations. The test occurred over water, and the vehicle was located only a few thousand feet above the surface during the parachute deployment phase for which photo-documentation was desired. This posed an additional difficulty for radar tracking, due to the radar multipath phenomenon present at low altitudes. Because of the small size of the test vehicle, manual visual target acquisition was not possible. Thus, radar aiding was required. Multiple sensors, all high-quality tracking radars, were used as the primary data source for this example. The optical sensor was slaved to a trajectory formed within the optimal estimator that utilizes simultaneous measurements from the multiple tracking radars. A timing flag, to synchronize the trajectory model and the actual vehicle trajectory, was available from a telemetry discrete.

Results of this example are similar to those shown in Section 3.1. Figure 7 illustrates slaving performance based on primary sensor data inputs only, with no model aiding. The radar solution was adequate in the early portion of the flight, before the onset of radar multipath. At low elevations, the radar multipath introduced unacceptable performance degradation. Figure 8 illustrates the performance of a model-aided tracker utilizing only the trajectory model, i.e., no radar data. In this case, the model error consisted of an incorrect vehicle drag coefficient. For purposes of illustration (Figure 8), perfect position initialization of the model-aided tracker was assumed. (To accomplish this would actually require radar or other initialization data). Figure 9 shows the improvement resulting from combining radar and model information. Figure 10 presents the result of combining all available information: radar data, model information, and operator updates.

The optimal filter produced a continuous estimate of vehicle velocity which was used in this investigation to compensate for time delays in the slaving commands due to data accuracy is degraded by processing and transmission delays, for the highly dynamic vehicle of this example, is shown in Table I.

Table I. Slave Pointing Accuracy Degradation due to Processing/Data Transmission Delay (with Compensation)

Delay	Degradation
0.2 sac	10%
0.6 sac	30%
1.0 sac	50%

As with the previous example, the model-aided tracker provides a technical solution which is otherwise unavailable with the given range resources.

4.0 SUMMARY AND CONCLUSIONS

This paper presents a technical concept called a model-aided tracker, which addresses the difficult problem of pointing a non-tracking sensor at a dynamic test vehicle under difficult test conditions such as high target dynamics, low altitude, and small target size. The model-aided tracker was evaluated via simulation studies and compared to alternative and/or conventional slaving methods. The model-aided tracker was shown to provide satisfactory results in test scenarios for which alternative/conventional techniques failed.

ACKNOWLEDGEMENT

Several individuals at Ball Systems Engineering Division supported the work described in this paper. Key contributors were Mr. Nicholas Albahri, Dr. Paul Kemp and Mr. Kirk Rozelle. The author appreciates the efforts of these and other individuals involved in the project.

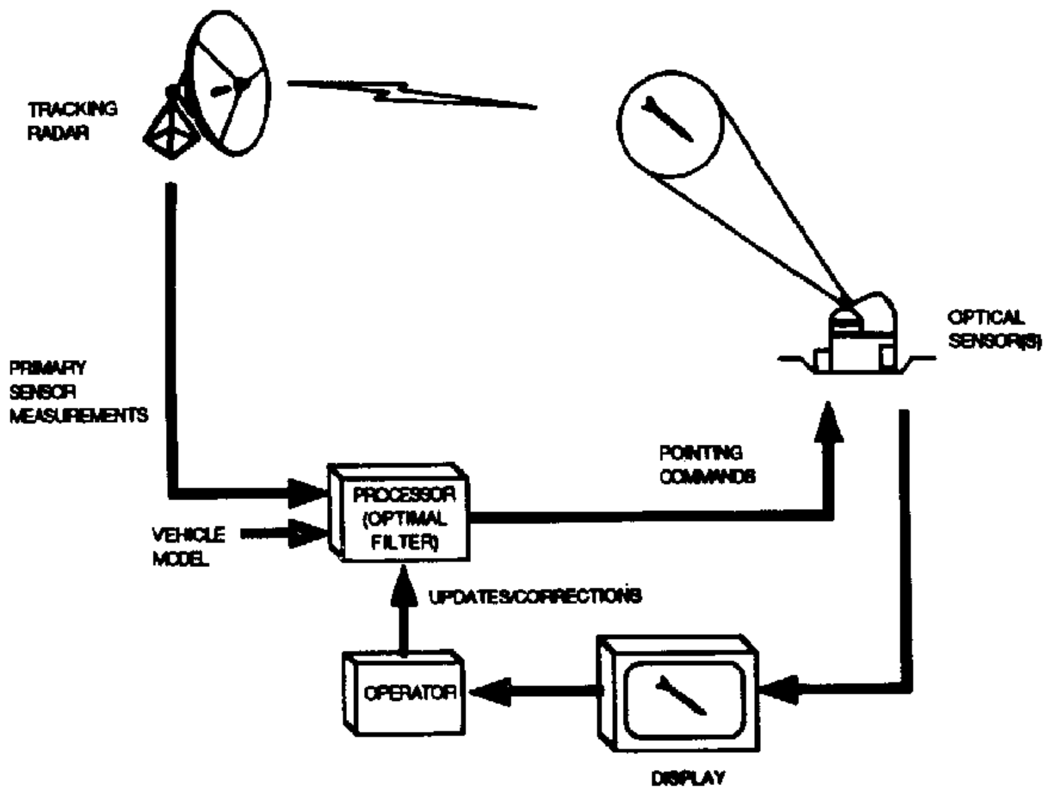

Figure 1. Model-Aided Tracker Concept

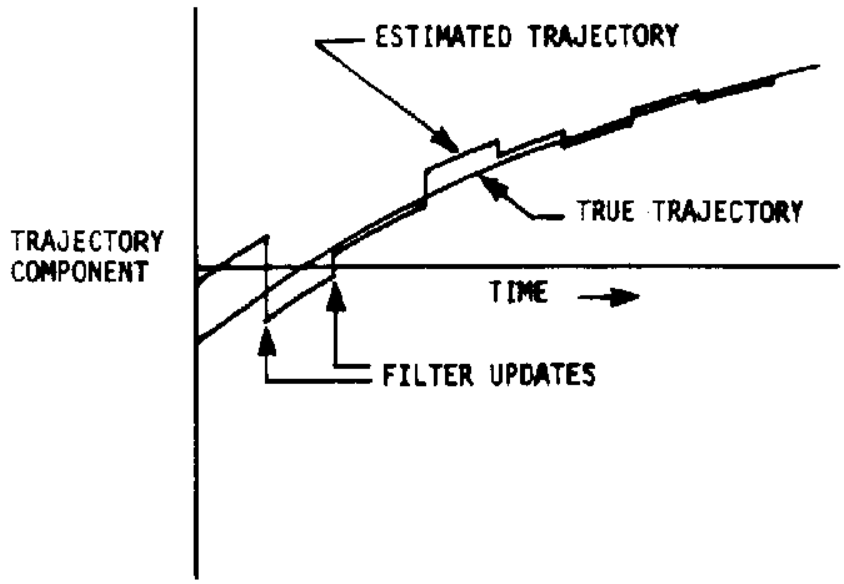

Figure 2. Role of Vehicle Trajectory Model in Model-Aided Tracker

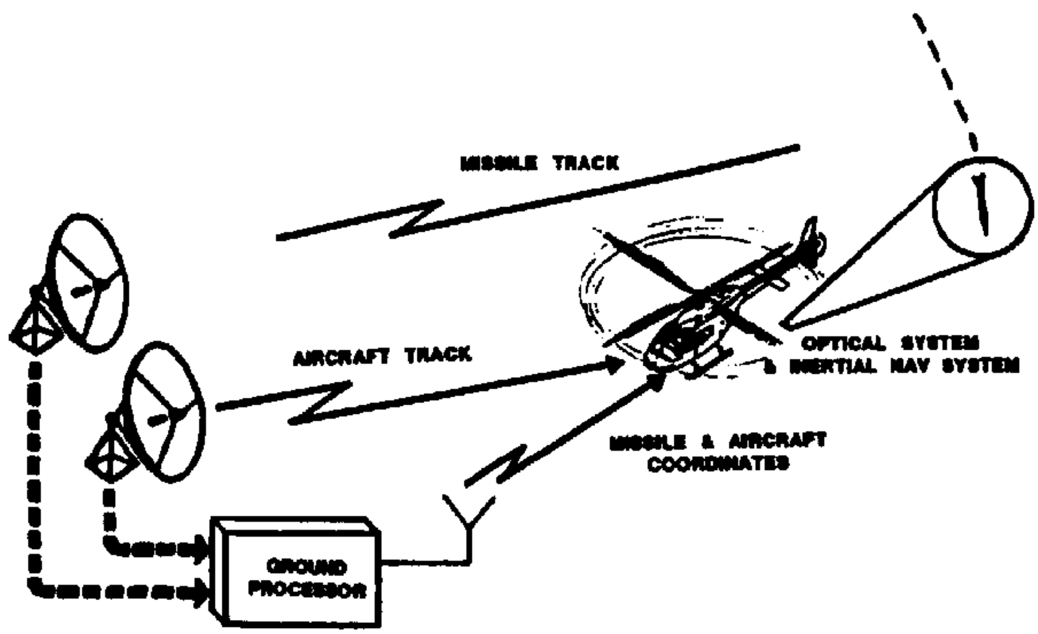

Figure 3. Airborne Slave Platform

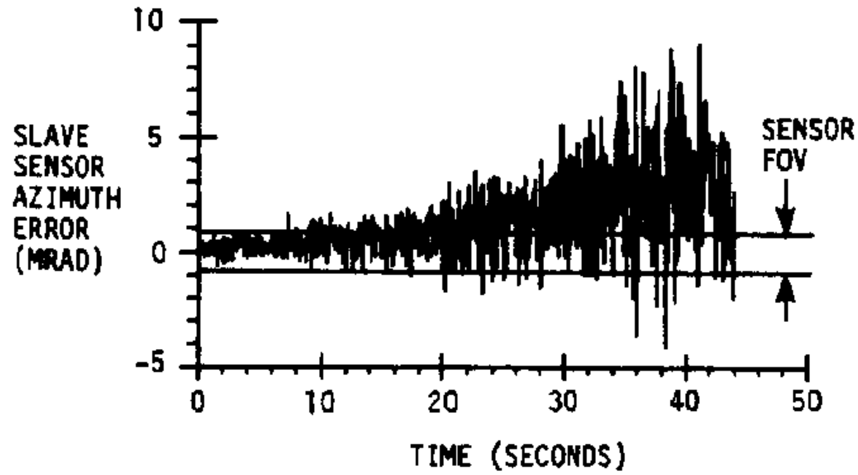

Figure 4. Raw Radar Input to Model-Aided Tracker

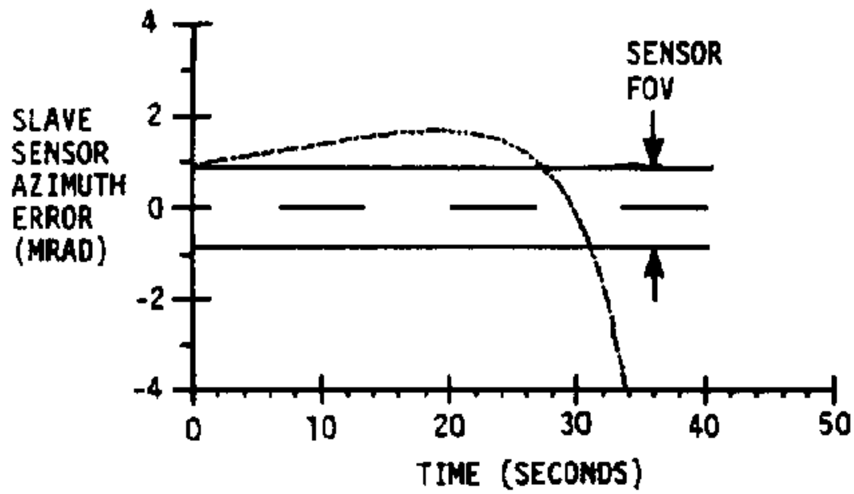

Figure 5. Model-Only Input to Model-Aided Tracker

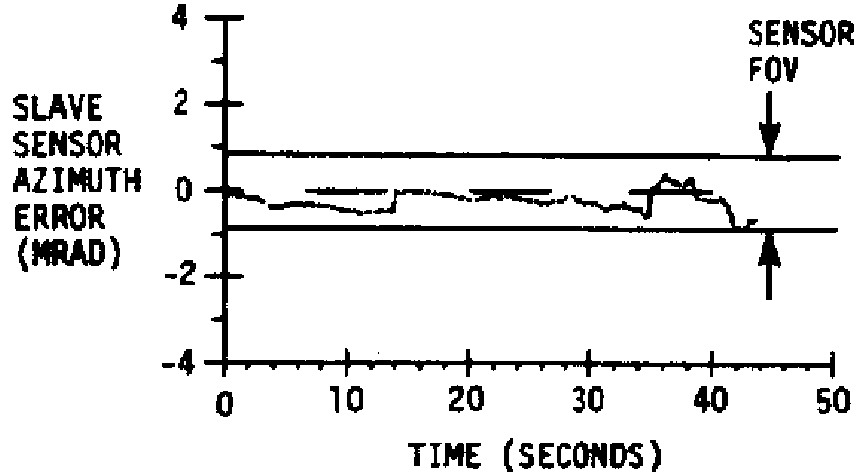

Figure 6. Full Implementation of Model-Aided Tracker
(Measurements, Model, Manual Inputs)

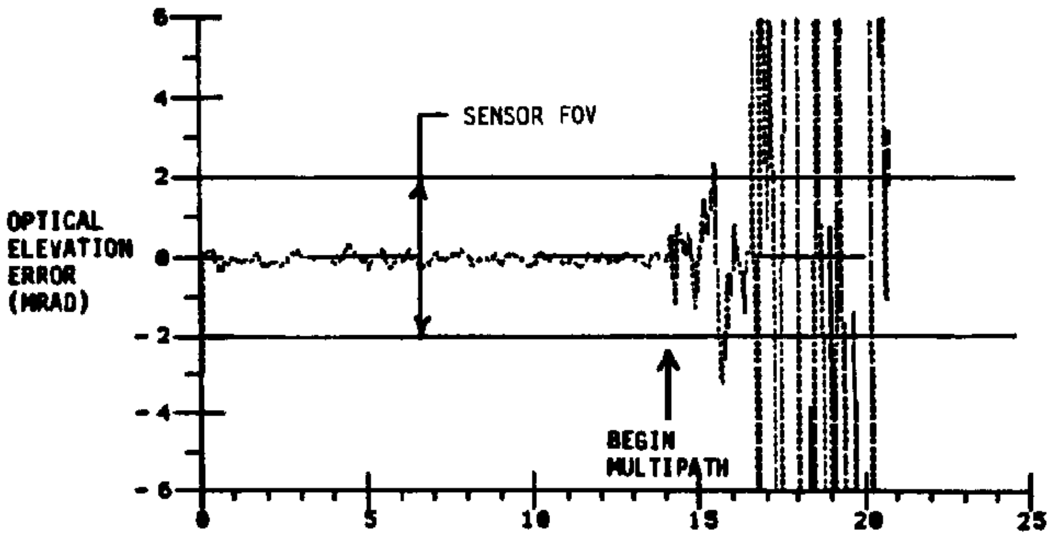

Figure 7. Single Radar, No Model

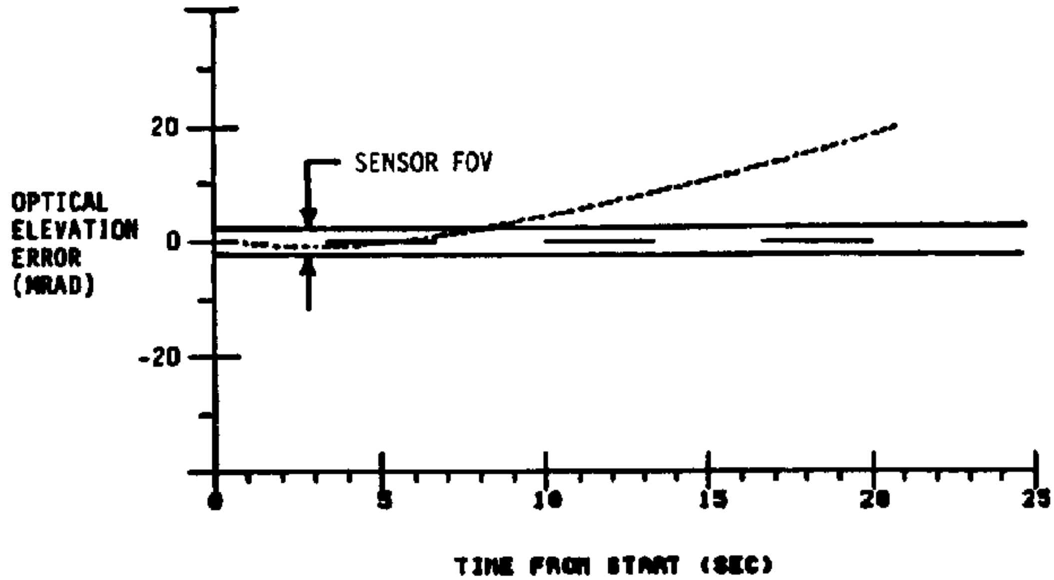

Figure 8. Model Only (No Radar) with 20% Drag Error
(Assumes Perfect Initialization)

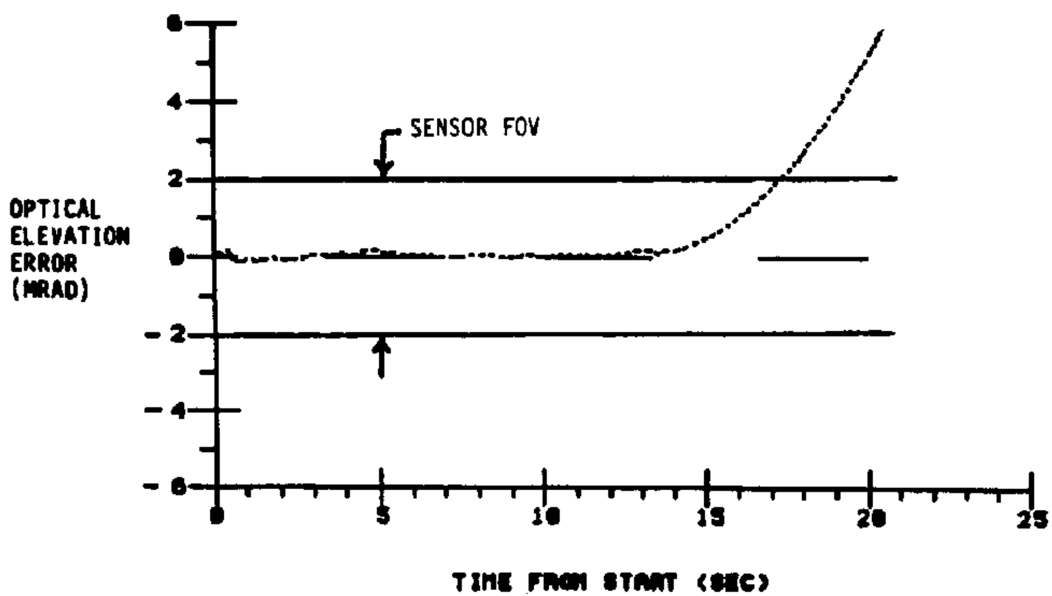

Figure 9. Single Radar Plus Modal, 20% Modal Drag Error

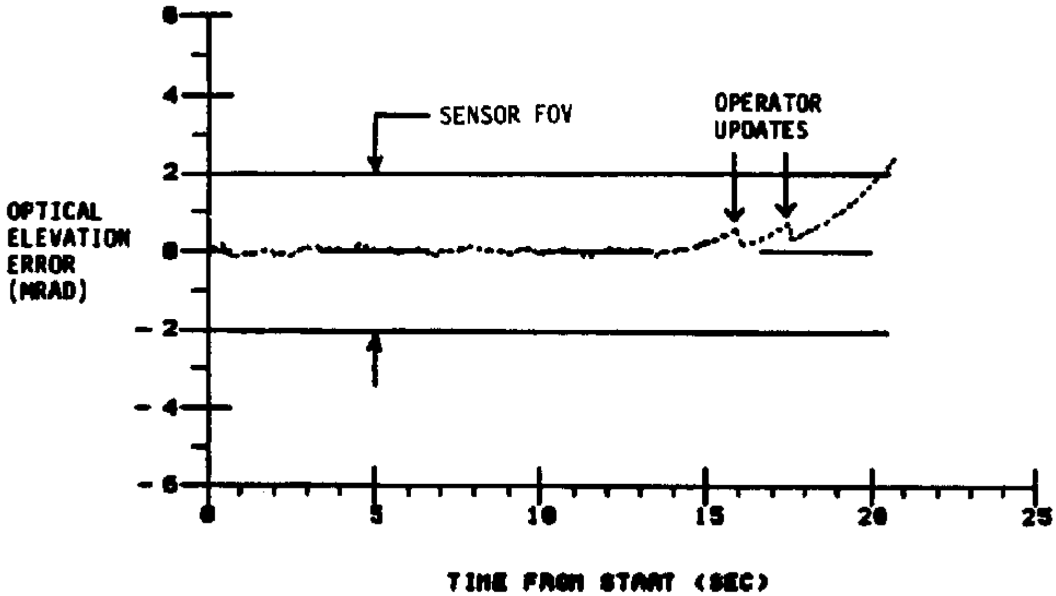

Figure 10. Single Radar Plus Model (20% Drag Error),
Two Operator Updates