Kalman Filter Aided Cooperative Optical Beam Tracking

Gokhan SOYSAL, Murat EFE

Dept. of Electronics Engineering, Faculty of Engineering, Ankara University, 06100, Tandogan, Ankara, Turkey

soysal@eng.ankara.edu.tr, efe@eng.ankara.edu.tr

Abstract. *In free-space optical communication between mobile terminals relative motion of the terminals requires an active mechanism to maintain optical alignment between the stations. Cooperative optical beam tracking could be used to address this problem. In this alignment scheme, each station tracks the arrival direction of its impinging beam to employ it as a guide to precisely point its own beam toward the opposite station. Tracking is achieved at each station by a quadrant photodetector which generates simultaneous azimuth and elevation error voltages. In this study a Kalman filtering assisted cooperative optical beam tracking has been proposed and its suitability to cooperative beam tracking is discussed. In this method, Kalman filter is employed to predict the alignment error that is used to produce appropriate control signals for re-alignment. Performance of the proposed method has been demonstrated through simulations.*

Keywords

Free space optical communication, Kalman filtering, cooperative beam tracking, fine pointing.

1. Introduction

Free space optical communication (FSOC) or optical wireless is quite a recent alternative to RF based communication systems [1]. It is a new form of communication where narrow laser beams are used to convey information from one point to the other. Although optical systems cannot yet completely replace RF communication systems, they do hold certain advantages over RF systems, which include, a higher bandwidth, a better confidentiality and immunity to interference, the major drawback is that, the performance deteriorates significantly with adverse atmospheric conditions.

An optical communication link using narrow laser beams requires reciprocal accurate pointing and spatial acquisition of the two stations prior to data transmission and reciprocal spatial tracking during transmission [2], [3]. Pointing is the act of aiming the transmitted beam toward the receiver within an acceptable accuracy. The purpose of spatial acquisition is to detect the transmitter's beam and align the normal vector to the receiving optical device with the direction of the impinging optical field. The reciprocal alignment may be aided by a return beacon from the receiver back to the transmitter, which also has to perform spatial acquisition to align properly its transmitting antenna. This cooperative acquisition phase is followed by a continuous reciprocal spatial tracking operation, which precisely compensates for the accidental relative motion of the two stations, due either to vibrations, turbulence, shocks, etc. [4], [5].

While optical communication between stationary terminals is relatively easy and less complicated; when the terminals are mobile some additional issues need to be considered. The main problem to be addressed in the mobile terminals case is keeping the terminals within each other's LOS independent of their motion. Such a task requires the dynamic tracking of the optical beam that is transmitted by the corresponding terminal. Beam tracking can be carried out either at one of the terminals or at both terminals depending on the communication requirements and the application. If the beam tracking is attempted at only one of the terminals then it is called single-ended beam tracking, where the receiver establishes a line of sight by tracking the arriving optical beam from the transmitter that is pointed towards itself. It is utilized when only one of the terminals is mobile. On the other hand, when two-way communication is required, i.e., when both terminals are mobile and they both transmit and receive, tracking is needed at both terminals thus, the technique of so called cooperative (or double-ended) beam tracking is employed. In a cooperative beam tracking system, the stations continuously track the arrival direction of the incident beam and transmit their beam back in that direction in which pointing errors may develop at both ends of the link and the pointing accuracy at one end affects the errors at the other end. The pointing errors at both ends, therefore, evolve as joint variables that are statistically related. While designing a system, precautions must be taken to address this problem. In general, beam tracking involves generation of error voltages corresponding to the changes in azimuth and elevation angles of the transceivers. These error voltages are generated by an optical sensor and ideally should be proportional to any offset alignment error between the receiver axis and the beam arrival that may occur. These error voltages will then be used to control both the azimuth and elevation alignments.

There have been numerous studies on cooperative tracking systems. For instance in [2], [3] and [4] the models that describe the position-sensitive photodetector by a deterministic input-output relationship and employ deterministic functions to characterize the relative motion of the stations were given. In [6], the steady state performance of the system was evaluated under a proportional control law whereas the stability properties of the deterministic model were studied in [4]. A simulink simulation of pointing control and tracking was given in [7] where it was shown that the proposed method had been able to maintain LOS between the terminals mounted on mobile vehicles that move in parallel or tandem. There exist other studies in the literature where an estimator is employed in FSO. For instance in [8], an alpha-beta filter is utilized for the optimization of the reacquisition process when the communication link between the platforms is broken. An extended Kalman filter (EKF) was used in [9] in order to estimate the relative position of the platforms using the measurements produced by a couple of high precision position sensing devices where the estimated position was used in axis alignment control. Both studies assumed that some information, namely, own position of the terminals in [8] and the produced control signals in [9], is communicated through a conventional wireless link. In [10], the EKF was used to estimate the disturbance, using the measurements obtained from the INS unit, in order to compensate for the relative motive motion of the optical communication systems mounted on the mobile terminals. This study investigates the suitability of employing a Kalman filter for predicting the tracking error in cooperative optical beam tracking for scenarios similar to those given in [7]. The main purpose is to produce better error signals, i.e., reduce the effect of noise on the error signals by using the Kalman filter where the noise on the error signals is generated primarily through signal shot noise, background noise, dark current noise and thermal (Johnson) noise mechanisms. Simulation results show that a suitably designed Kalman filter can successfully produce prediction of the angle errors where the predictions are improved in comparison to the error values produced by the detector.

This paper is organized as follows. Section 2 outlines the transceiver structure and how the error voltages are produced whereas Section 3 describes the Kalman filter. Scenarios are given in Section 4 and simulation results are presented in Section 5 where some concluding remarks are given in the Conclusions section.

2. Laser Beam Pointing and Tracking

In optical communication when the physical channel is unguided -such as free space- the optical system usually has a very narrow transmit/receive beamwidth in order to fully realize its performance potential. Therefore, spatial pointing and tracking become important issues in the design of such systems.

As previously mentioned, depending on the type and direction of the communication, optical tracking systems can be employed either at the receiving and/or the transmitting end of the optical link. Fig. 1 shows the basic receiver/transmitter (transceiver) structure in an optical communication system, where FOV stands for Field of View, θ is the FOV angle, A is the detector area and a is the laser spot diameter. The transceiver comprises a position sensitive photodetector (e.g. quadrant detector) in association with a filter and a focusing lens (employed at each station in cooperative tracking) to measure the azimuth and elevation components of the tracking error.

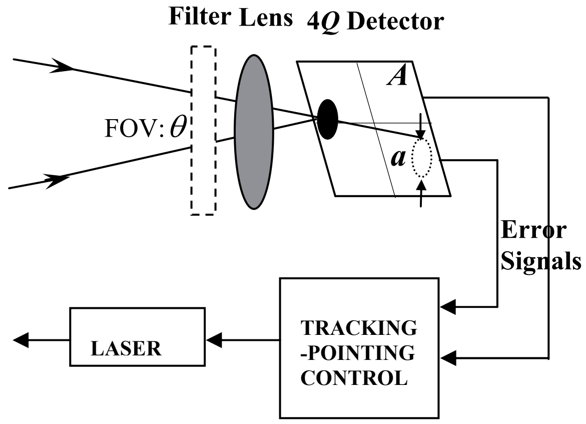

Fig. 1. Basic transceiver structure.

The tracking error is the displacement of the beam's arrival direction with respect to the direction normal to the receiving aperture. A servo-driven pointing assembly adjusts the heading of the transmitting optical device (in azimuth and elevation directions) according to the measured tracking error. The lens is used to collect the widened laser beam to form a spot on the detector. An optical filter can be placed in front of the lens in order to filter out any signal from an unwanted light source. The quadrant detector acts as the position-sensing element and is the most essential element in producing the tracking error in both azimuth and elevation. Tracking error is used to generate the error-control signals from the received optical beam. Each quadrant on the detector produces a voltage output proportional to the laser energy that falls onto it. Hence, the detector is able to detect a defocused laser spot moving over its surface in two dimensions as shown in Fig 2. The error voltages in azimuth and elevation are given by (1) and (2) respectively

$$E_X = \frac{(V_3 + V_4) - (V_1 + V_2)}{E_T}, \tag{1}$$

$$E_Y = \frac{(V_1 + V_4) - (V_2 + V_3)}{E_T} \tag{2}$$

where $$E_T = V_1 + V_2 + V_3 + V_4. \tag{3}$$

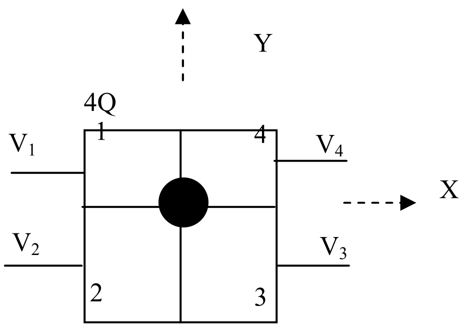

Fig. 2. Quadrant detector outputs for error voltage calculations.

Any offset from the center of the position sensitive detector produces a control error voltage, i.e., E_X and/or E_Y in the axis in which it occurred, creating a drive voltage to the actuator used that will position the laser beam back to the null position i.e., $E_X = E_Y = 0$. The control signals then command two servo-loops in the tracking control unit for the control of azimuth and elevation movements. The aim is to keep the incoming beam properly centered on the quadrant detector independent of the relative motion between the transmitter and receiver. E_T, given by (3) is used for normalizing the error signals with respect to the changing laser beam intensity.

3. The Kalman Filter

Kalman filter is the traditional and most widely used state estimator [11]. The Filter is the general solution to the recursive linear minimum mean square estimation problem and it provides optimal tracking performance provided the following conditions [12] are met; *i)* the state of the target evolves according to a known linear dynamic model driven by a single known input and additive zero-mean, white Gaussian noise with known covariance and *ii)* the measurements are linear functions of the target state corrupted by additive zero-mean, white Gaussian noise with known covariance.

Assuming that the target dynamic process can be modeled in discrete Markov form, then the equation that describes the target dynamics in terms of a Markov process can be written as,

$$X(k+1) = FX(k) + \Gamma V(k) \tag{4}$$

where $X(k)$ is the k dimensional target state vector, F is the known transition matrix, Γ is the known disturbance transition matrix and $V(k)$ is the unknown zero-mean Gaussian process noise with assumed known covariance Q. Measurements are a linear combination of the system state variables and corrupted by uncorrelated noise. Thus, the m dimensional measurement vector is modeled by

$$Z(k) = HX(k) + w(k) \tag{5}$$

where H is the $m \times k$ measurement matrix and $w(k)$ is zero mean, white Gaussian measurement noise with covariance R. Note that, it is assumed that $V(k)$ and $w(k)$ are mutually uncorrelated. A good derivation of the Kalman filter equations can be found in [13], here only the resulting standard Kalman filter equations [12], [14] are given.

$$\tilde{X}(k+1|k) = F\hat{X}(k|k), \tag{6}$$

$$v(k+1) = Z(k+1) - H\tilde{X}(k+1|k), \tag{7}$$

$$P(k+1|k) = FP(k|k)F' + \Gamma Q \Gamma', \tag{8}$$

$$S(k+1) = HP(k+1|k)H' + R, \tag{9}$$

$$W(k+1) = P(k+1|k)H'S(k+1)^{-1}, \tag{10}$$

$$\hat{X}(k+1|k+1) = \tilde{X}(k+1|k) + W(k+1)v(k+1) \tag{11}$$

$$P(k+1|k+1) = P(k+1|k) - W(k+1)S(k+1)W(k+1)'. \tag{12}$$

In (6) through (12) $\tilde{X}(k+1|k)$ and $P(k+1|k)$ are the predicted state and state covariance respectively $\hat{X}(k+1|k+1)$ and $P(k+1|k+1)$ are the updated state and state covariance respectively. $S(k+1), R, W(k+1)$ and $v(k+1)$ are the covariance of the innovation, the covariance of the measurement noise, the Kalman gain and the innovation respectively. Recursive estimation structure of the Kalman filter is given in Fig. 3 where it is clearly seen each time instant a prediction of the state is produced.

4. Scenarios

In this study we consider two vehicles that are in motion and carrying an optical transceiver structure illustrated in Fig. 1 installed on them on a rigid platform. Three scenarios have been created where the vehicles are assumed to be moving in tandem, i.e., as in a convoy, or in parallel and communicating with each other through the optical link.

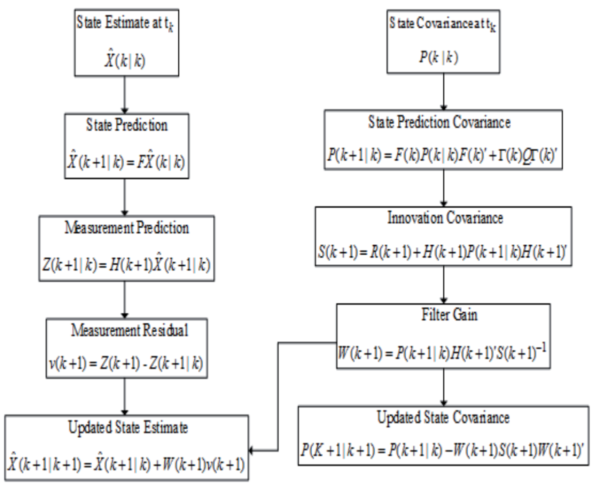

Fig. 3. Basic Kalman filter flowchart.

The first scenario models two vehicles that are 25 m apart from each other, moving in parallel. In the scenario the first vehicle starts its motion from its initial position (1000 m,1000 m,0 m) moving towards +X direction with 10 m/sec constant velocity. The constant velocity motion of the vehicle is assumed to obey Discrete White Noise Acceleration (DWNA) model [15], in which small perturbations to vehicle speed in either direction are allowed. Constant velocity motion of the vehicle lasts for 30 sec, then it starts its coordinated turn motion [15] at 2.25 deg/sec constant angular velocity for 40 sec completing a 90 deg turn. Then it moves at constant velocity for another 30 sec. The second vehicle is assumed to move in coordination with the first vehicle trying to keep the 25 m distance at all times. Thus, it starts its motion at the initial position of (1000 m, 1025 m, 0 m) in +X direction at 10 m/sec constant velocity and advances for 30 sec then it performs a coordinated turn motion for 36 sec at a constant angular velocity of 2.5 deg/sec after which it concludes its motion with 30 sec of constant velocity motion. Trajectories of both vehicles are depicted in Fig. 4.

The second scenario models two vehicles moving in tandem where there is 30 m distance between the two vehicles. The first vehicle starts its motion from its initial position of (1000 m, 1000 m, 0 m) and moves in +X direction for 30 sec at 10 m/sec constant velocity according to the DWNA motion model. The vehicle then increases its velocity for 1 sec at an acceleration of 2 m/sec^2 at +Z direction and moves for 19 sec at its new velocity after which it slows down at an acceleration of -2 m/sec^2 for 1 sec resuming its original velocity. The vehicle concludes it motion with another 50 sec of constant velocity motion in +X direction. The second vehicle is assumed to follow the same trajectory 30 m behind the first vehicle. The second scenario is representative of two vehicles in convoy going up a hill where the alignment error in elevation changes significantly. Vehicle trajectories are illustrated in Fig. 5.

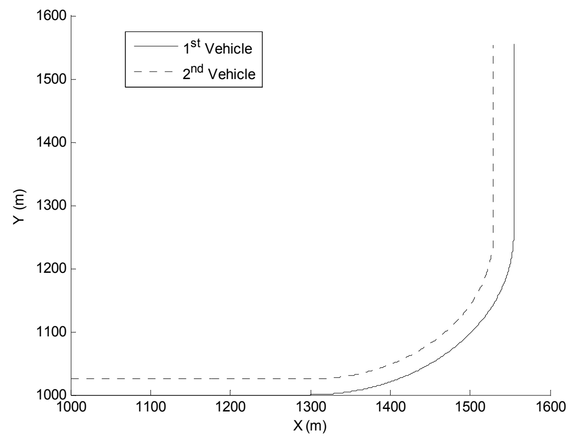

Fig. 4. Scenario 1.

For the third scenario we recall the first scenario as the motion of the first vehicle in the third scenario is exactly same as that of the first vehicle in the first scenario. The difference here is the assumption that the vehicles are no longer moving in parallel but in tandem. The second vehicle is assumed to follow the first vehicle with 30 m distance completing the same motion as the first vehicle does. In the third scenario the alignment error in azimuth changes significantly. The vehicle trajectories are given in Fig. 6.

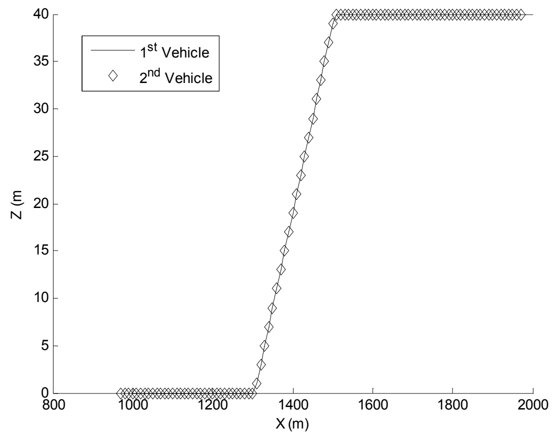

Fig. 5. Scenario 2.

5. Simulation Results

Simulation studies aim to show that the use of Kalman filtering could be used to produce the necessary control signals to properly align to optical stations installed on mobile vehicles for uninterrupted communication.

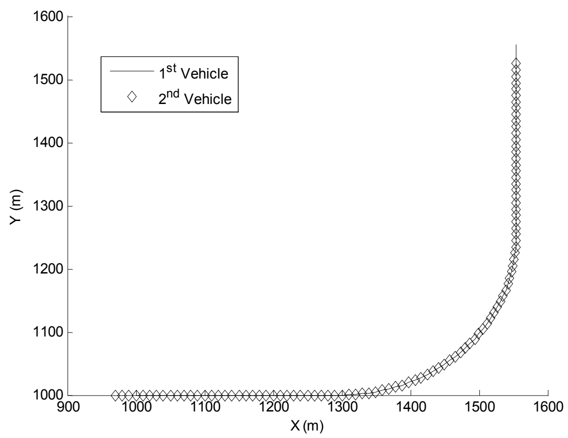

Fig. 6. Scenario 3.

Assuming that the error voltages produced by the photodetector are obtained at discrete times, these voltages have been fed to the Kalman filter as measurements and the changes in these voltages relative to the vehicle motion has been estimated. Assuming that θ and φ represent the azimuth and elevation alignment errors produced by the photodetector respectively, the state space model that show the evolution of these errors in time are given in (13) and (14)

$$x(k+1) = f(x(k)), \quad (13)$$

$$z(k+1) = h(x(k+1), w(k+1)) \quad (14)$$

where k is the discrete time index, x is the state vector, z is the measurement vector, f is the state transition function, h is the measurement function and w is the additive, zero mean, white Gaussian measurement noise with a known variance. The state and measurement vectors are shown in (15) and (16) respectively.

$$x = \begin{bmatrix} \theta & \dot{\theta} & \varphi & \dot{\varphi} \end{bmatrix}' \tag{15}$$

$$z = \begin{bmatrix} \theta & \varphi \end{bmatrix}' \tag{16}$$

Studies with the scenarios described in the previous section revealed that the change in relative azimuth and elevation positions of the vehicles during their coordinated motions remains linear. This validates the use of linear Kalman filter equations given in Section 3. Moreover, the linear model is also justified in [5] based on the fact that the system operates over small angles during the fine control regime. Following the linear assumption, the functions *f* and *h* given in (13) and (14) can be given as;

$$F = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 0 \end{bmatrix}, \quad H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \tag{17}$$

where T is the rate at which the measurements are taken.

The Kalman filter that has been designed to estimate the alignment errors caused by the relative motion of the vehicles assumes that the error voltages, i.e., measurements, are taken at 1 sec time intervals. This may seem like a slow rate as optical transceivers can produce alignment error much faster, however, we would like to display that even with slow rates the Kalman filter performs better. This result is particularly important as this rate with long distance communication systems will be even slower. Error voltages are assumed to be corrupted with zero mean Gaussian white noise with known standard deviation of 3 deg/sec. Kalman filter design parameters, namely the process noise covariance Q that defines the sensitivity to unexpected changes, and the measurement noise covariance R, are described as

$$R = \begin{bmatrix} 10 & 0 \\ 0 & 10 \end{bmatrix}, \quad Q = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}. \tag{18}$$

In the simulations it assumed that the stations are properly aligned prior to vehicles start their respective motions and the Kalman filter is initialized with the measurements taken at this stage according to two point differencing method [12]. Then, the initial state and state covariance for the Kalman filter employed are given as;

$$\hat{x}(0) = \begin{bmatrix} 0 & 0 & 0 & 0 \end{bmatrix}'$$

$$P(0) = \begin{bmatrix} 10 & 10 & 0 & 0 \\ 10 & 20 & 0 & 0 \\ 0 & 0 & 10 & 10 \\ 0 & 0 & 10 & 20 \end{bmatrix}$$

1000 Monte Carlo runs have been performed for the tracking of laser beam alignment error with Kalman filter and the RMS prediction error produced by the Kalman filter has been given as the measure of performance. The average prediction error is analogous to measurement noise standard deviation and is the indicator of how accurate the azimuth and elevation errors can be obtained. Improvement in the accuracy of the error signals is directly related to the control signals to be produced.

The relative azimuth angle variation and the corresponding Kalman filter prediction in scenario 1, where two vehicles perform constant velocity and coordinated turn motions in parallel, are given in Fig. 7.

As Fig 7 illustrates, the Kalman filter can successfully predict the azimuth angle variation due to the relative motion of the vehicles. RMS errors in azimuth and elevation with respect to the measurement error for the same scenario are depicted in Figs. 8 and 9 respectively.

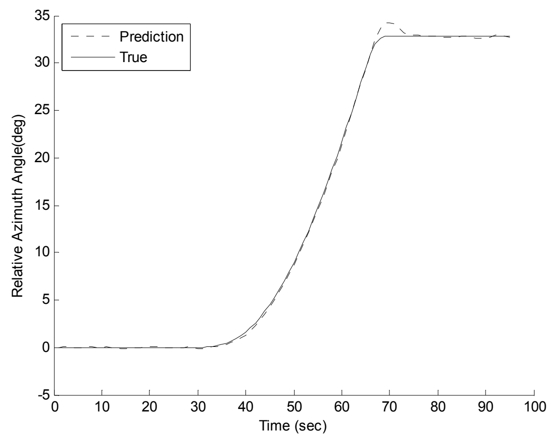

Fig. 7. Variation of relative azimuth angle for scenario 1.

In these figures the solid line is the standard deviation of the measurement error and dashed line is the RMS error of the Kalman filter prediction. Fig. 8 reveals that the predicted azimuth error is better than that of produced by the photodetector, i.e., measurements, except for the times when the motion starts and coordinated turn concludes.

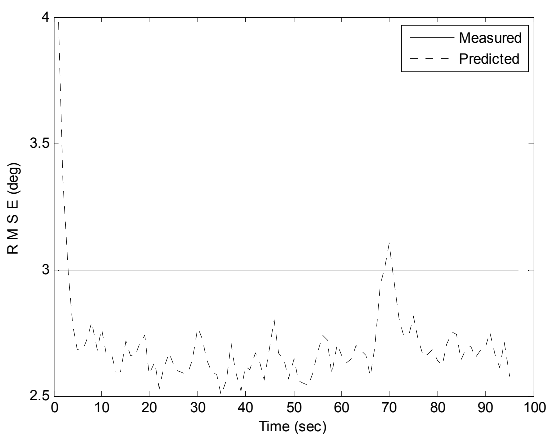

Fig. 8. RMS azimuth error for Scenario 1.

A similar result has been obtained for the elevation error as well, however, since no motion in Z axis is assumed Kalman filter prediction for elevation error is better than that for azimuth error. The significance of these results lie in the fact that more precise error voltages could be obtained from the Kalman filter even before the misalignment occurs due to the relative motion of the vehicles.

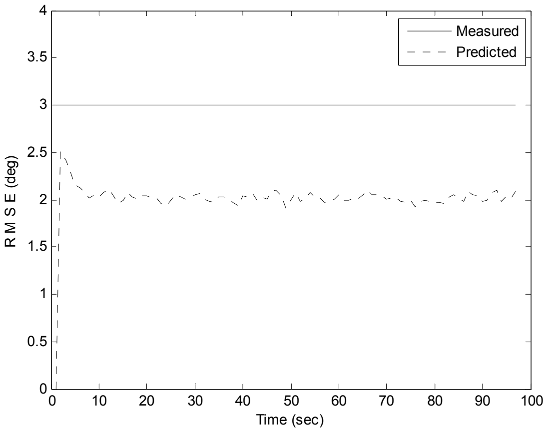

Fig. 9. RMS elevation error for Scenario 1.

Scenario 2 is created in order to investigate the effect of any variation in elevation angle error. Since, this time the targets' relative motion is in Z axis only the elevation angle change and the related Kalman filter prediction is shown in Fig. 10. As it can be seen in Fig. 10 prediction at the beginning and end of the maneuver displays a jump due to that fact that vehicles start and end maneuvers at different times as they are moving in tandem.

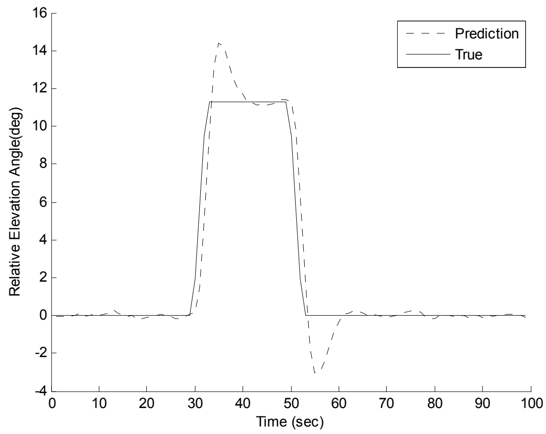

Fig. 10. Variation of relative elevation angle for Scenario 2.

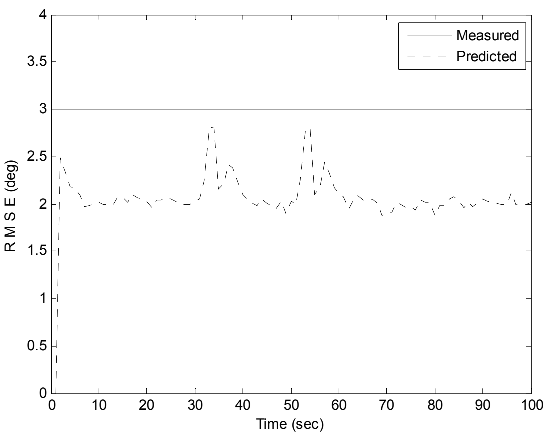

Fig. 11. RMS elevation error for Scenario 2.

However, as it is depicted in Fig. 11, even at times when these jumps occur in prediction the RMS error of the prediction is still better that the values produced by the photodetector. Since there is only limited variation in azimuth, the RMS prediction error is not given.

In Scenario 3 error voltage variation for vehicles moving in tandem and maneuvering in XY plane is investigated. Variation of the azimuth error signal and the corresponding Kalman filter prediction is shown in Fig. 12. As expected maneuver start and maneuver end periods are the worst in terms of both prediction and RMS prediction error. However, unlike the results obtained for Scenario 2, RMS azimuth prediction errors are worse than the azimuth errors produced at the output of the quadrant detector at maneuver start and stop.

Nevertheless, the predicted RMS error values quickly recover and become better than that of the error signals produced by the quadrant detector following maneuver start and stop. Elevation error predictions are very similar to that of obtained for Scenario 1, hence, they are not presented here.

Simulation studies conducted with three scenarios that are different in nature have revealed that, both azimuth and elevation errors can be predicted more precisely than the values produced by the photodetector with the use of Kalman filtering. As far as the three scenarios are concerned, Kalman filter predictions have provided about 15% improvement in azimuth and 31% improvement in elevation in comparison to the values obtained at the output of the quadrant detector. The performance decrease problem caused by the maneuver could be addressed by the use of Kalman based multiple filters such as the Interacting Multiple Model (IMM) algorithm [12]. The utilization of multiple filters would help producing improved prediction throughout the vehicle maneuver.

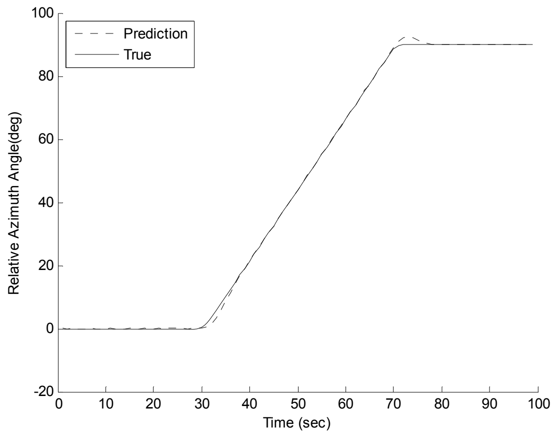

Fig. 12. Variation of relative azimuth angle for Scenario 3.

Moreover, Kalman filter is a stochastic tool where the state vector could be expanded to include any stochastic parameter that would affect the system operation and/or output of the position sensing detector. Thus, any other parameter could be estimates along with the error voltages. Also, although this study only deals with the optical beam tracking in short distance communication, the use of Kalman filter can easily be extended to long distance communication applications such as intersattelite communication. However, in long distance communications state equation become nonlinear and the use of linear Kalman filter would produce poor predictions. In this case the extended Kalman filter that is proposed for nonlinear estimation could be used.

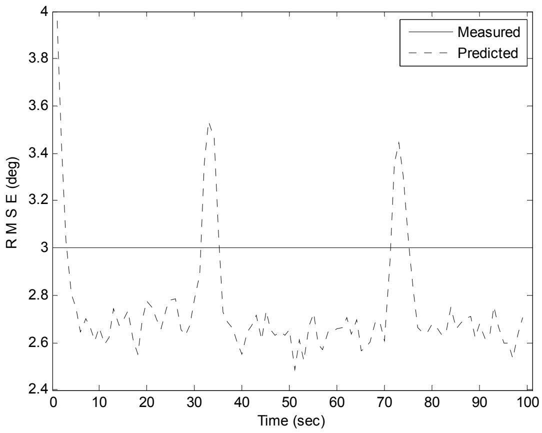

Fig. 13. RMS azimuth error for scenario 3.

6. Conclusions

In this study the use of Kalman filtering in cooperative optical beam tracking is investigated. Three scenarios have been created in order to test the suitability of Kalman filtering in optical beam tracking applications. Simulation results have revealed that the Kalman filter can successfully predict the error voltages caused by the relative motion of the optical communication stations. In cooperative optical beam tracking, these error signals are used to command the servos for re-alignment. Simulation results also showed that the predicted error voltages are improved with respect to the values obtained at the output of the position sensitive detector.

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About Authors

Gokhan SOYSAL received his B.Sc. and M.Sc. degrees in Electronics Engineering from Ankara University, Turkey in 2002 and 2005 respectively. He is currently studying towards his Ph.D. at the same university. He has been working as a research assistant at the Electronics Engineering Department of Ankara University since 2002. His research interests include multi-target multi-sensor tracking and detection, multi-static sensor networks, sensor management, information based decision and estimation.

Murat EFE received his B.Sc. and M.Sc. degrees in Electronics Engineering from Ankara University, Turkey in 1993 and 1994 respectively. He received his Ph.D. degree from the University of Sussex, UK in 1998. He worked as a post doctoral fellow at Ecole Polytechnique Fédérale de Lausanne in Switzerland following his Ph.D. degree. He has been with the Electronics Engineering Department at Ankara University since 2000 where he both teaches and conducts research. His research interests include Kalman filtering multi-target multi-sensor tracking, detection and estimation, cognitive radar, passive network sensing, optical beam tracking.