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A Kinematics Update State Hypotheses Information Surveillance Model for a Moving Train

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Abstract: A train is more difficult to track and control accurately in low satellite visible environment. This is due to greater sensitivity to control inputs, multipath loss and line of sight of Global Positioning System. The paper presents the performance analysis of Differential Global Positioning System measurement using Kalman filter for accuracy of three meter. Designing the tracking controller for train which is constrained to move in predefined direction and velocity Simulation is carried out using Mat Lab and Visual Kalman filter window. The initial track observed for 60 samples along horizontal and vertical direction with data loss of only 0.0005% inaccuracy.

Keywords- Differential GPS, KUSHI model, Kalman filter.

I. Introduction

The railway is one of the biggest transportation systems in the world. For the efficient and safe transportation, modernized physical layout and advanced communication infrastructure are essential to support the transportation. Tracking, location reporting, speed, time synchronization, signaling and controlling etc. are the key factors of an intelligent rail operation management. The communication systems play a major challenging role in the biggest rail transportation system. [1][2]. For the last few decades, many researchers have done lot of work on train tracking, with measurement of speed and velocity in satellite visible environment using Space based radio navigation system called Global Positioning system (GPS). It is one of the advanced technologies which is widely used for tracking, positioning, surveying and navigation. It is of more accurate, precise, efficient, low cost and less maintenance demand [3].

However many came to the conclusion that GPS technology is not suitable for low satellite visible environment such as forest, urban canyons, tunnel, mountains, deep cuttings etc. The Line Of Sight (LOS) between transmitter and receiver and multipath loss in such areas results in lesser accuracy in real time application [4]. The use of Differential Global Positioning System (DGPS) is to identify specific location of the train which improves the accuracy to higher level. DGPS operated with both roving receivers which calculate satellite position and stationary receivers that use these measured position to compute signal timing [5].

.Differential GPS use multiple receivers to increase measurement accuracy. The mobile receivers calculate their absolute positions with increased accuracy by altering their received satellite measurements in co-ordination with base station. Nowadays Kalman filters have been widely used in DGPS receivers. The Kalman filter is an optimal estimator which is used for real time dynamic data processing [6]. Recent advances in Wireless Sensor Network (WSN) with GPS technology are considered in [7]. Author in [7] explains in detail how the accuracy of GPS navigation and tracking system detoration due to line of sight and multipath losses. To overcome this, in [7] a conventional statistical test method and differential outlier detection method is proposed. In [8] WSN tracking control system is proposed where a fuzzy observer-based tracking control is designed for time delay non-linear distributed parameter system. Author [8] highlighted range and range-rate measurement for multi target tracking with uncollected information. The main drawback of above system is that is not suitable for tracking, signaling and controlling the train in satellite visible and low satellite visible area more accurately. To overcome this drawback, this research work proposes Kinematics Update State Hypotheses Information (KUSHI) model to track the train accurately and precisely in satellite visible and non- visible environment

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The organization of the paper is as follows. Section (2) explains the overview of DGPS measurements and the method to analyze the system. Section (3) explains KUSHI model to measure the kinematics of moving train. The state modeling assumption is based on the movement of the train with constant and varying kinematic parameters. Section (3.1) explains the problem formulation to track the moving train using Kalman filter. It also explains tracking state model and measurement. Section (3.2) explains the algorithm to test Kalman filter model theoretically. Section (4) explains simulation set up using Mat lab and Visual Kalman filter window along with nominal parameter. Section (5) depicts results and analysis of the moving train's position and velocity graph with related state errors. Section (6) depicts concluding remarks.

2. Overview of Differential GPS measurements

DGPS position accuracy is measured up to 2m, by partly removing atmospheric condition and system errors. DGPS receiver receives signal from the satellites and correction signals from reference source or base station. The measuring accuracy is gradually decreases as the rover moved away from the base station.

Trilateration and Triangulation are the two analytical methods used for tracking and navigation application. Trilateration use only distance measurement to identify the position of objects where as Triangulation use angles and distance to locate an object. The application of these two analytical tracking and navigation method to a dynamic system have some disadvantages like distance measurements become very fluctuating and noisy which in turn make localization becomes more difficult. This requires a suitable filter to remove the unwanted noise signal for the better location accuracy of train. The Kalman filter is the best approach that provides optimal estimation of the system state vector that is mainly applied to the navigation application like DGPS receiver position and velocity determination.

Kalman Detection / Estimation Technique Kalman filter is linear estimator. It automatically detects the presence of moving objects and estimates the kinematics such as position, velocity and acceleration with desired degree of accuracy. It provides an efficient methodology to estimate the state of process, it supports estimation of past, present and future states [….k-2, k-1, k, k+1, k+2…]

3. Proposed Kinematics Update State Hypotheses Information (KUSHI) Model

Figure (1) applied for real time dynamic data processing system. Estimation using Kalman filter depends on prior knowledge of train location using both process and measurement model.

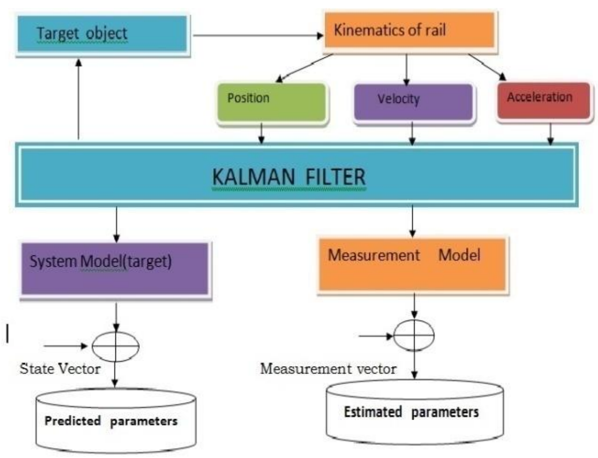


Fig1: KUSHI Model

3.1 Problem formulation to track the moving train using Kalman filter

In this work, the problem formulation is concentrated on the train which is constrained to move in straight line with constant velocity. Let x (i) and x' (i) are the train position and velocity respectively. Let v (i) be the measurement noise which observe the position of train. The train is moving with constant speed x'' (i) = 0.The system states are position, velocity and acceleration.

The state parameters are [X,Y,Z] where X= Position, Y= Velocity, Z= Acceleration

Tracking State Model

X (i+1) = A X (i) + B u (i)…………..(1) Where A = system transition matrix

B= process noise gain matrix

$$\mathbf{A} = \begin{bmatrix} 1 & \delta t & \delta t^2/2 & \delta t^3/3 \\ 0 & 1 & \delta t & \delta t^2/2 \\ 0 & 0 & 1 & \delta t \\ 0 & 0 & 0 & 1 \end{bmatrix} \qquad \mathbf{B} = \begin{bmatrix} \delta t^3/3 \\ \delta t^2/2 \\ \delta t \\ 1 \end{bmatrix}$$

δt is a sampling interval

X (i+1) = A X (i) + B u (i)

$$\begin{bmatrix} x(i+1) \\ x'(i+1) \\ y(i+1) \\ y'(i+1) \end{bmatrix} = A \begin{bmatrix} x(i) \\ x'(i) \\ y(i) \\ y'(i) \end{bmatrix} + B \begin{bmatrix} u_x(i) \\ u_{x'}'(i) \\ u_y(i) \\ u_{y'}(i) \end{bmatrix}$$

If the time interval is from i to i-1, then the tracking state model equation becomes

X (i) = A X (i-1) + B u (i-1)…………..(2)

A and B matrices remains same.

Where E {u (i) }= 0 and Variance{u (i) } = M,

Where M = Target model noise co-variance matrix.

Measurement Model

Y(i) = C X (i) + V (i)…………………..(3) Where C is sensor output

$$C= \begin{bmatrix} 1 & \delta t & \delta t^2/2 & \delta t^3/3 \\ 0 & 1 & \delta t & \delta t^2/2 \\ 0 & 0 & 1 & \delta t \\ 0 & 0 & 0 & 1 \end{bmatrix} \qquad \text{If } \delta t=0 \quad C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\begin{bmatrix} Y_x(i) \\ Y_x'(i) \\ Y_y(i) \\ Y_y'(i) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x(i) \\ x'(i) \\ y(i) \\ y'(i) \end{bmatrix} + \begin{bmatrix} v_x(i) \\ v_x(i) \\ v_y(i) \\ v_y(i) \end{bmatrix}$$

E {v (i) }= 0, Variance{v (i) } = N Where N is Measurement noise co-variance matrix

Prediction updates

Filter predicts the state and variance at time i+1 based on information at time i. This is also known as time updates. The equations are responsible for projecting forward the current state and error covariance estimates to obtain the priori estimates for the next time step.

1. State Prediction: $\hat{X}\,(^{i+1}/_{i})=A\,\hat{X}\,(^{i}/_{i})$
2. Prediction Covariance: $\tilde{P}(^{i+1}/_{i}) = A\,\tilde{P}\,(^{i}/_{i})\,A^T + M\,(i)$

Measurement updates

Kalman filter updates the state and variance using combination of the predicted state and the observation Y (i+1). These equations are responsible for the feedback which incorporates new measurement in to priori estimate to obtain an improved posteriori estimate.

1. State estimate : $\hat{X}\,(^{i+1}/_{i+1}) = \tilde{X}(^{i+1}/_{i}) + K\,[Y_i - C\tilde{X}\,(^{i+1}/_{i})\,]$
2. Estimation Co-Variance: $\hat{P}\,(^{i+1}/_{i+1}) = [I-KC]\;\hat{P}(^{i+1}/_{i})$

Gain matrix

To minimize the conditional mean-squared estimation error with respect to the Kalman gain.

Kalman gain: $K = \hat{P}\,(^{i+1}/_{i})\,C^T\,[\,C\,\tilde{P}\,(^{i+1}/_{i})\;C^T + N]^{-1}$

Kalman filter model tested theoretically by assuming the parameters;

Equation (1) and (3) are tested theoretically by assuming the values of

1. Constant Model with A= 1
2. Control Variables are set to B, U = 0
3. The measurement matrix C=1
4. The process is Scalar with N= n , P= p and M= m. Assumes Gaussian White noise.

With these values, the following algorithm (1) is tested to verify the modeling accuracy.

3.2 Algorithm (1)

State Prediction: $\hat{X}\,(^{i+1}/_{i})=A\,\hat{X}\,(^{i}/_{i})$

Prediction Covariance: $\tilde{P}(^{i+1}/_{i}) = A\,\tilde{P}\,(^{i}/_{i})\,A^T + M\,(i)$

State Estimate : $\hat{X}\,(^{i+1}/_{i+1}) = \tilde{X}(^{i+1}/_{i}) + K\,[Y_i - C\tilde{X}\,(^{i+1}/_{i})\,]$

Estimation Co-Variance: $\hat{P}(^{i+1}/_{i+1}) = [I-KC]\ \hat{P}(^{i+1}/_{i})$

Kalman gain: $K = \hat{P}(^{i+1}/_{i})\, C^T [\, C\, \tilde{P}(^{i+1}/_{i})\ C^T + N]^{-1}$

Where the initial values are, System Noise M = 0.0001, Measurement Noise N = 0.1, X_0=0 and P_0 = 1000

4. Simulation Setup

The tracking accuracy is determined by the movement of train in straight line with constant and varying velocity. To perform this, algorithm (2) given below is applied. Simulation is carried out using Visual Kalman Filter window and Mat Lab. Visual Kalman Filter set up is a filtering design for windows and provides visual method to estimate the state of process or removes noise from data.

Adopted Algorithm (2)

Function Value [$X_{prediction}$, $P_{prediction}$] = Predict (X,P,A,M)

$X_{prediction} = A^* X$;

$P_{prediction} = A^*P^*A^1 + M$;

Function Value [Difference, T] = Dynamic ($X_{prediction}$, $P_{prediction}$, Y,C,N)

Difference = Y-C* $X_{prediction}$;

$T = N+C * P_{prediction} *C^1$

Function Value [X_{KUSHI}, P_{KUSHI}] = Dynamic @ update ($X_{prediction}$,$P_{prediction}$,Diff, T,C)

$K= P_{prediction} *H^1*T^1$

$X_{KUSHI} = X_{prediction}$ +K*Difference

$P_{KUSHI} = P_{prediction} - K*T*K^1$

Nominal Parameters used in algorithm

Sensor Location - S_1 – [0,0,0] S_2 – [60,0,0]

Positional Measurement error - X direction= 0.0001 m

Sampling interval – 1 sec

Initial track reading - 0.8

Process Noise Covariance = 0.8 * Measurement error covariance

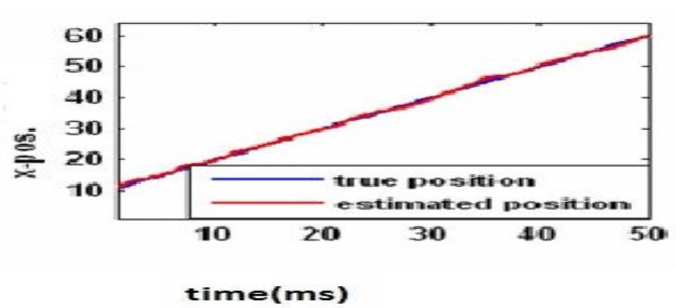
Initial State Estimate Covariance = Position Variance = 0.1 [X, Y]

Velocity Covariance = 0.0001 [X, Y]

5. Results and Analysis

(A) Position estimation graph

Figure (2) shows simulation results of position of the train moving in straight line (X direction) and its corresponding state error. Simulation is carried out for run of 60 samples. Results demonstrate that estimated state will be closer to true position value if the model is create based on the true situation, . When the train along X direction then position state error is +0.5 at t=30ms and -1 at t=35ms. It is conclude that the data loss is less, when the train tracks along X direction and produce only 0.005 % inaccuracy.



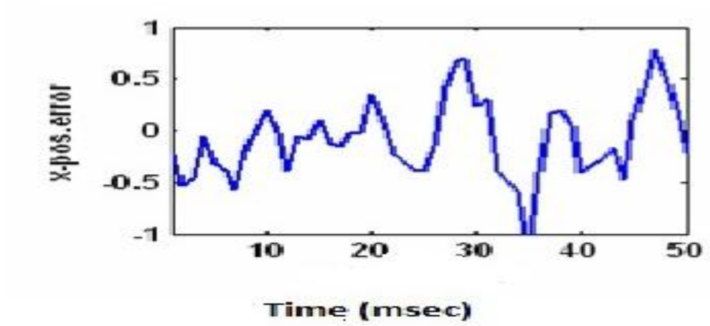


Fig. 2 Train along X position and position state errors

Figure (3) shows simulation results of position of the train moving in straight line (Y- direction) and its corresponding state errors. The experiment is carried out in 50 msec for 60 samples. When train is moving in Y-direction, the estimated position is much closer to true measurements. The state errors occurred are +0.5 and -0.5 at t=3msec and t=40msec.It is conclude that the position state errors occurred when train is moving in Y-direction is inverse to that of X-direction state errors and produce only 0.005% inaccuracy.

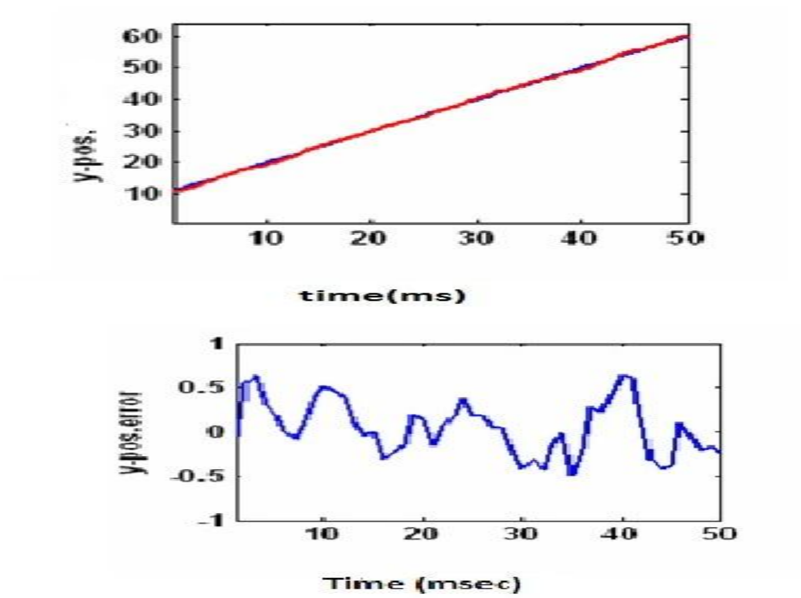


Fig 3 Train along Y position and position state errors

(B) Velocity estimation graph

Figure (4) and Figure (5) shows the simulation result of Velocity Estimation measurements when the train is moving in straight line. The simulation is carried out using 6 samples. Results demonstrate that estimated velocity measurements is getting close to the true velocity value and has less error than measurement noise. There is no much variation along X direction but is very noticeable along the Y direction as expected. It is conclude that initial velocity jerk at (+1.3) and the corresponding state errors at (-0.5) when the train is moving in X-direction. Similarly when the train is moving in Y-direction, initial velocity jerk at (-1.3) and the corresponding state error is within 0.05 of the true value, even though the measurements are between 0 and 2.

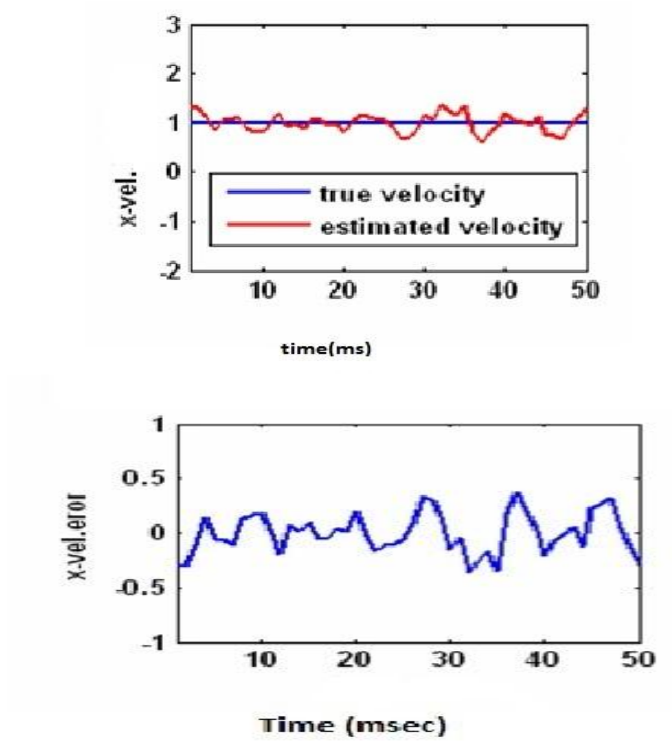


Fig 4 The velocity of train along X position and velocity state errors.

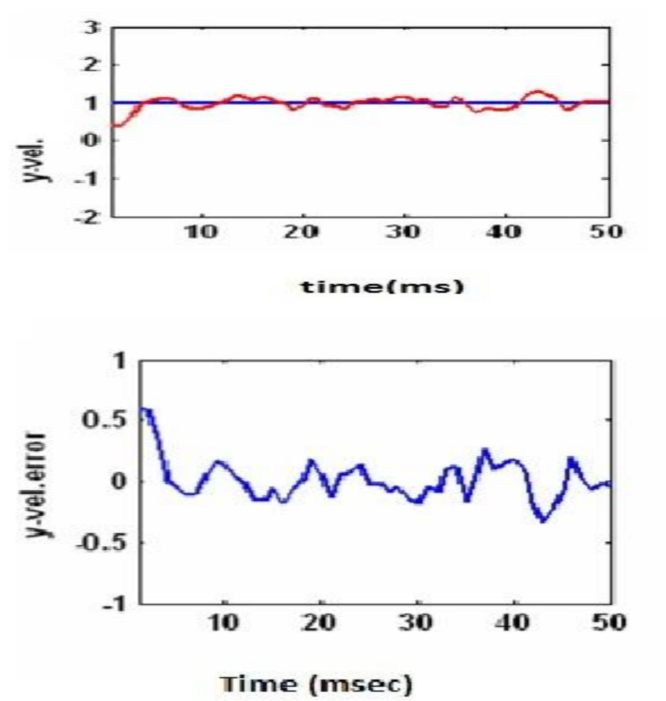


Fig 5 The velocity of train along Y position and velocity state errors.

6. Concluding remark

In this paper, KUSHI design based on Kalman filter theory was elaborated and applied for the DGPS accuracy measurements. It has been demonstrated that when a train is moving in a straight line with constant and varying velocity, results in data loss of only 0.005% inaccuracy. Simulation is carried out using Mat lab. The overall design is part of an ongoing research design and integration of tracking train model. For future research direction, it is interesting to explore the integrating DGPS with wireless communication devices in a single model, is possible to achieve the autonomous identification of train location from the remote places as and when required. It is demonstrate and compare the accuracy of the tracking system with individual technology.

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