AN INTELLIGENT VEHICLE LOCATION SENSING SYSTEM USING KALMAN FILTER APPROACH

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ABSTRACT

An intelligent vehicle may be defined as a vehicle that senses the environmental conditions which in turn produces some automatic action. The ability to accurately detect a vehicle's location and its status is the main goal of automobile trajectory monitoring systems. These systems are implemented using several hybrid techniques that include: wireless communication, geographical positioning and embedded applications. A Kalman filter is an optimal estimator - i.e. infers parameters of interest from indirect, inaccurate and uncertain observations. It is recursive so that new measurements can be processed as they arrive.

Keywords**: *Adaptive Cruise Control, Global Positioning System, Kalman Filter, Position Estimator, State Space Method.***

I. INTRODUCTION

The intelligent systems concept seems to be very popular among transport management systems. Continuously increasing amount of vehicles in road, air and marine transport areas has put research in this area. Efficient, economical and more intelligent methods have to be deal with these challenging problems. The available intelligent system is vehicle platoons. In this framework research has been carried out in control and sensory requirements for platoons of vehicles. In this platform, vehicles are having shorter spacing between them. However, spacing with constant value is stable only if certain types of vehicle to vehicle communications are possible (Swaroop et al., 1994). This requires radio communication devices. Vehicle recognition plays an important role in field of traffic monitoring. It includes location identification, behavior identification of vehicles. Conventional loop detectors and video based systems are inefficient. The adaptive cruise control uses radar and stereovision sensing methods to detect the distance in defined environment (Kato et al., 2002). The smooth response filters out traffic disturbances and reduces air pollution and fuel consumption. This paper investigates the methods of location sensing systems. The paper is organized as follows. Section II gives an overview of location identification. Section III and IV describes the proposed Kalman filter approach and design of Kalman filter for location sensing respectively. In section IV, experimental results are presented, and conclusions are given in section V.

II. LOCATION SENSING SYSTEMS

Positioning systems determine the location of a person or an object either relative to a known position or within a coordinate system (G. M. Djuknic and R. E. Richton, 2001). In the last few decades, various positioning systems have been motivated by demand and have been developed. The comparison of different position estimators are shown in Table 1.

TABLE 1: Comparison of Different Position Estimators

Estimator	Advantages	Disadvantages
ML	High Accuracy	Global solution is not guaranteed Noise statistics are needed
LLS	Global solution is guaranteed Noise statistics are not needed	Low Accuracy
NLS	High Accuracy Noise statistics are not needed	Global solution is not guaranteed
WLLS	Global solution is guaranteed High Accuracy can be achieved	Noise statistics are needed

Some of the applications of positioning systems include (but are not limited to) law enforcement, security, road safety, tracking personnel, vehicles, and other assets, situation awareness, and mobile ad hoc networks. As shown in Fig. 1 positioning systems can be classified into two categories as global positioning and local positioning. Global positioning systems (GPS) allow each mobile to find its own position on the globe. A local positioning system (LPS) is a relative positioning system and can be classified into self - and remote positioning. Self - positioning systems allow each person or object to find its own position with respect to a static point at any given time and location. An example of these systems is the inertial navigation system (INS). Remote positioning systems allow each node to find the relative position of other nodes located in its coverage area. Here, nodes can be static or dynamic. Remote positioning systems themselves are divided into active target remote positioning and passive target remote positioning.

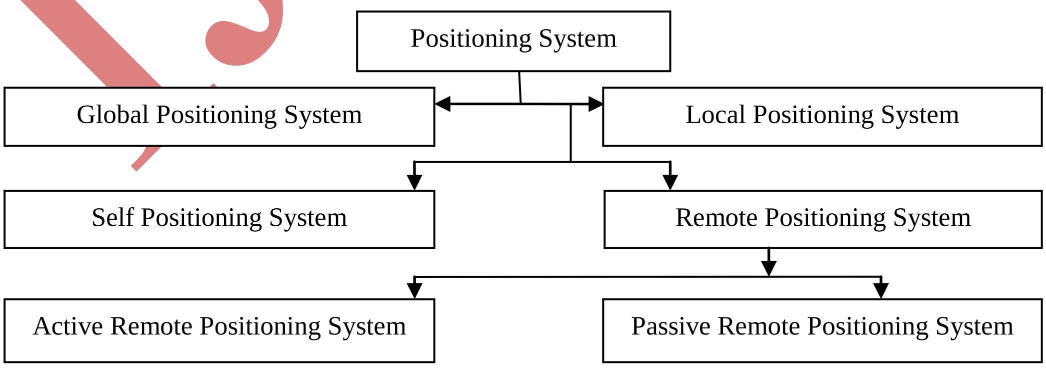

Fig.1: Positioning Sensing Systems

Location based technologies have been used for a number of years. However, advances in wireless technologies in location based technologies. It is possible to open a range of applications. The global positioning system finds the position of objects which are stationary or moving. Tracking systems have central processor that monitors the location of objects (B.T. Fang, 1986). The performance of location sensing system is dominated by its accuracy as a measure of systems expected error in terms of distance, Precision as a measure of expectation of location within the accuracy and Latency as a measure of how long it takes for a system to produce an estimate for a single location.

An analytical solution is the straightforward method to determine the position. It involves using a series of functions. The new expression used to calculate estimates the position. Measurement error is results from noise effects of the system due to analytical solutions. Suppose there is a mathematical model and to understand its behavior and to find a solution to the set of equations. The best is the use calculus, trigonometry, and other math techniques to write down the solution. Now the model will behave under any circumstances can be found. This is called the analytic solution, because analysis is used to figure it out. It is also referred to as a closed form solution.

Numerical solutions are iterative algorithms provided solutions where analytical solutions not exist. For more complex models, the math becomes much too complicated. Then numerical methods are used of solving the equations, such as the Runge-Kutta method. For a differential equation that describes behaviour over time, the numerical method starts with the initial values of the variables, and then uses the equations to figure out the changes in these variables over a very brief time period. It's only an approximation, but it can be a very good approximation under certain circumstances. It start with some initial information about variable x of $f(x) – g(x) = 0$. The problem of solving x is called as root finding as the solutions for roots, or zeros. It includes the bisection method and Newton Raphson Method. But, these solutions are not applicable for measurement error. Error minimization algorithm works by minimizing the difference between real world observations and predicted values of model equations which are called as errors or residuals. Errors are due to interference and instrumental noises. It finds the solution with lowest minimization error and it gives the optimal solution for the given data. Thus error minimization is also called as optimization algorithms. Simulated annealing and Particle Swarm Optimization called as stochastic algorithms can be used where the derivative of the error function is difficult for error minimization. This technique is used in real time position sensing. But, error minimization techniques are resource hungry for location sensing systems (S. Kirkpatrick, C. D. Gelatt, M. P. Vecchi, 1983). State space methods can be used to estimate the state of deterministic systems including physical processes like swing of pendulum or level of liquid. In location sensing, the position and movement of moving vehicle or object are considered (R. E. Kalman, 1960). States are a set of parameters that describe the instantaneous condition of a process at a set point of time. These methods predict the current state using model and the previous states and then corrects the predicted current measurements. These are also called as recursive time domain filters as they use temporal models. The feedback is based upon Markov assumptions. It is possible to provide estimates in real time environment as state space methods do not required storing long histories of states.

III. KALMAN FILTER APPROACH FOR VEHICLE LOCATION SENSING

A Kalman filter is an optimal estimator which infers parameters of interest from indirect, inaccurate and uncertain observations. It is recursive so that new measurements can be processed as they arrive as batch processing where all data must be present. Kalman filter is one of the most popular state space algorithms (C.K. Chui and G. Chen, 1987). It is an efficient algorithm used in real time navigation and positioning systems. Since the time of its introduction, the Kalman filter has been the subject of extensive research and application, particularly in the area of target tracking. This is likely due in large part to advances in digital computing that made the use of the filter practical, but also to the relative simplicity and robust nature of the filter itself. As a fruitful application for state estimation, the problem of tracking a moving object from radar measurements has received a great deal of attention in the literature. However a number of problems are still open, and reducing computational requirements, while achieving some desired tracking performance is another important issue in many practical applications.

The kalman filter is an implementation of Bayes' rule that is a way of updating the stochastic properties of the system for given input. Usually a Cartesian coordinate system is well suited to describe the target dynamics since the dynamic equations are often linear and uncoupled. Within the significant toolbox of mathematical tools that can be used for linear state estimation from noisy sensor observations, one of the most often-used tools in the target tracking field is what is known as the Kalman Filter (Hushino et al., 1996). But, because measurements of the target location are expressed as nonlinear equations in coordinates, the tracking problem is connected with nonlinear estimation. The natural way to generalize the methods applied to linear estimation was to extend the Kalman Filter to nonlinear recursive equations: this classical extended algorithm is called the Extended Kalman Filter. These two algorithms are the foundation of most moving vehicle tracking algorithms, but they have a lot of important flaws that need to be addressed.

The Kalman filter is essentially a set of mathematical equations that implement a predictor-corrector type estimator that is optimal in the sense that it minimizes the estimated error covariance-when some presumed conditions are met. Rarely do the conditions necessary for optimality actually exist, and yet the filter apparently works well for many applications in spite of this situation. The Kalman Filter has made a dramatic impact on linear estimation because of its adaptivity for implementation on a digital computer for on-line estimation and usefulness of the state-space approach. Today, the Kalman Filter is an established technique widely applied in the fields of navigation (Feng, Huifang, et al., 2014), guidance (Gao, Lian Zhou, 2014), aircraft (V. Gavrilets, A. Shterenberg, M.A. Dahleh, E. Feron, 2000), and missile tracking (D. Williams, B. Friedland, J. Richmans, 1983), reentry of space vehicles, etc.

The Kalman Filter is the foundation of our moving vehicle tracking method, because of it's adaptively for implementation on a digital computer for on-line estimation and usefulness of the state-space approach. The state-space equations are decomposed into two parts: the state equation and the measurement equation. The state equations describe the target dynamics and are chosen in order to be linear.

IV. DESIGN OF KALMAN FILTER

Designing a kalman filter to solve the problem of location sensing are known as the state transition and the measurement equations. The state transition equation known as the difference equation, describes the evolution of the process over time. It predicts the state changes between measurements. This equation models the dynamics of the object being positioned and will be different for different systems. The state transition equation is in the form:

$$\hat{X}_k = A_K X_{K-1} + w \tag{1}$$

where A_K is state transition matrix to calculate prediction for the current state vector $\hat{X}_k$ and X_{K-1} is the previous state vector. A_K is an NXN matrix. w_{k-1} is the normally distributed noise. The measurement equation allows the filter to predict measurements. The general form of measurement equation for position sensing is as:

$$\hat{Z}_k = H_k \hat{X}_k + v_{k-1} \tag{2}$$

where $\hat{Z}_k$ is the state prediction by the measurement sensitivity matrix H_k. H_k is an MXN matrix with M as measurements in number. v_{k-1} is the normally distributed measurement noise. The difference of $Z_k - \hat{Z}_k$ is the measurement residual. Firstly, integrate the measurements. Then, the Kalman filter predicts the confidence in the given state. It is measure of how accurately the filter estimates the state vector as:

$$\hat{P}_k = A_k P_{k-1} A_k^T + Q_k \tag{3}$$

where P_k is known as the apriori estimate of the covariance. Q_k is the covariance matrix for the noise w. It is added with the effect of decreasing the confidence in the state. The Kalman filter then calculates the Kalman gain matrix K which is a weighting factor to optimally integrate the measurements:

$$Y_k = \left(H_k \hat{P}_k H_k^T + R_k\right)^{-1} \tag{4}$$

where Y_k is the information matrix to incorporate the weight of the measurement noise by the addition of the measurement covarianceR_k. R_k is the covariance of the zero mean noise v.

$$K_k = \hat{P}_k H_k^T Y_k \tag{5}$$

where K_k represents the Kalman gain with multiplication of information matrix, measurement sensitivity matrix and a priori system covariance. The factor determines how the measurements will influence the state to detect or reject outlying measurements by:

$$\hat{z}_k = H_k \hat{x}_k \tag{6}$$

Finally, the Kalman filter integrates the measurement with the state:

$$x_k = \hat{x}_k + K_k(z_k - \hat{z}_k) \tag{7}$$

The filter uses the Kalman gain to update the current system covariance:

$$P_k = (I - K_k H_k)\hat{P}_k \tag{8}$$

where I is the identity matrix. The system covariance first expands with the passage of time and the contracts as the observation is integrated. For non-linear systems, more general representation is used. For example, the process equation relates the previous state to the current state:

$$\hat{x}_k = f \tag{9}$$

The measurement equation relating the state of measurements as:

$$\hat{z}_k = h(\hat{x}_k, v_{k-1}) \tag{10}$$

One such non linear Kalman filter is the extended Kalman filter (S.J. Julier, J.K. Unlmann, H.F. Durrant, 1995). It used first order Taylor series approximation to the process and measurement equations. Another, nonlinear Kalman filter is unscented Kalman filter (J.J. Laviala, 2003). It performs the sampled representations of mean and covariance through f ( ) and h ( ). It is easy to implement and more accurately models non-linear transformations.

V. EXPERIMENTAL RESULTS

The vehicle is initially located at the point x = 0 and moves along the X axis with velocity varying around a constant speed 10m/sec. The motion of the vehicle can be described by a set of differential equations:-

$$\dot{x}_1 = x_2, x_1(0) = 0 \tag{11}$$

$$\dot{x}_2 = w, x_2(0) = 10, w \sim N(0, (0.3^2)) \tag{12}$$

where x_1 is the position and x_2 is the velocity, w the process noise due to road conditions, wind etc.

Problem: Using the position measurement to estimate actual velocity. The position of the vehicle is measured at every dt = 0.1 seconds. But, because of imperfect aperture, weather etc., the measurements are noisy, so the instantaneous velocity, derived from 2 consecutive position measurements (remember, we measure only position) is inaccurate. The Kalman filter is an accurate and smooth estimate for the velocity in order to predict train's position in the future. The state space equation after discretisation with sampling time dt and the measurement model as:-

$$x_{k=1} = \phi_{x_k} + w_k, \qquad \phi = e^{A\Delta t},$$

$$A = [0\ 1\ ;0\ 0], w_k\ N(0, Q) \qquad , Q = [0\ 0; 0\ 1] \tag{13}$$

$$y_{k=1} = [1\ 0]x_{k+1} + v_k, v_k \sim N(0,1) \tag{14}$$

Fig. 2 shows the position and velocity estimation results with Kalman estimated displacement and Kalman estimated velocity respectively. The key idea is to consider the accelerations not as inputs to the system, but as states, in the model. Besides, in that model, the accelerations are modeled as a weighted sum of the previous accelerations. A linear fitting is recursively performed using an LMS algorithm. The computed model (state transition matrix, state error covariance matrix) is then used in a classic Kalman filter that has the vehicle position and several accelerations as its outputs.

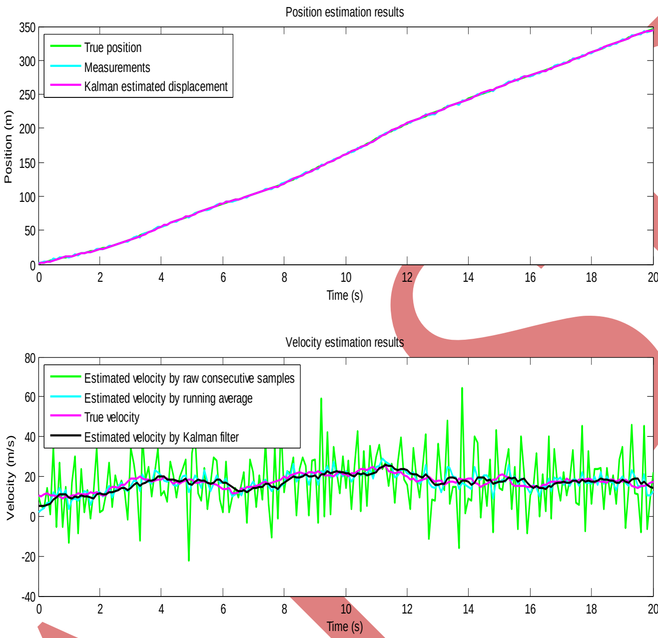

Fig. 2: Position and Velocity Estimation with Kalman Estimated Displacement and Velocity

VI. CONCLUSION AND FUTURE SCOPE

In order for the Kalman Filters to be applicable, the assumption that the random variables have Gaussian probability distributions is used. We then consider that, after they propagate through the nonlinear functions, they are still Gaussian. Even if the approximation is accurate to at least the second order with the Unscented Transformation, the assumption is still wrong. To avoid those assumptions in the target tracking problem, the particle filter can be used. The Particle Filter is a sequential Monte Carlo based method that allows for a complete representation of the state distribution, using sequential importance sampling and resampling. It makes no assumption on the form of the probability densities in question, i.e. full nonlinear, non-Gaussian estimation. Nevertheless, the implementation of the Particle Filter is not yet very efficient. Research needs to be done in order for this algorithm to be implemented in hardware, and eventually be used in target tracking purposes.

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Biographical Notes

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