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# Use of Kalman Update Algorithm for vivid enhancements of GPS and navigation

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***Abstract: GPS navigation has become one of the primary needs in a smart phone or any device which is compatible with finding out location of your marker. We discuss the issues related to the positioning of a particular object or person, the problem of navigation to find it and also the scope for improvement. In this paper, we describe and delinquent how to use Kalman Update Algorithm for better positioning and update of location long with a smoother navigation of marker.***

***Keywords: GPS navigation, KDGPS Kalman filter, Kalman Smoothing Update.***

## I. Introduction

Signal Simulation Toolbox to provide users with a GPS signal generation capability at a much lower cost than currently available on the market. The novel differential GPS algorithm for a network of users that has been developed in this research uses a Kinematic Differential Global Positioning System (KDGPS) approach. A network of mobile receivers is considered, one of which will be designated the 'reference station' which will have known position and velocity information at the beginning of the time interval being examined. The measurement situation on hand is properly modeled, and a centralized estimation algorithm processing several epochs of data is developed. The effect of uncertainty in the reference receiver's position and the v level of the receiver noise are investigated. Simulations are performed to examine the ability of the algorithm to correctly estimate the non-reference mobile users' position and velocity despite substantial satellite clock errors and receiver measurement noise [1].

More formally, the Kalman filter operates recursively on streams of noisy input data to produce a statistically optimal estimate of the underlying system state. The algorithm works in a two-step process. In the prediction step, the Kalman filter produces estimates of the current state variables, along with their uncertainties. Once the outcome of the next measurement (necessarily corrupted with some amount of error, including random noise) is observed, these estimates are updated using a weighted average, with more weight being given to estimates with higher certainty. Because of the algorithm's recursive nature, it can run in real time using only the present input measurements and the previously calculated state; no additional past information is required. From a theoretical standpoint, the main assumption of the Kalman filter is that the underlying system is a linear dynamical system and that all error terms and measurements have a Gaussian distribution (often a multivariate Gaussian distribution).Extensions and generalizations to the method have also been developed, such as the extended Kalman filter and the unscented Kalman filter which work on nonlinear systems. The underlying model is a Bayesian model similar to a hidden

Markov model but where the state space of the latent variables is continuous and where all latent and observed variables have Gaussian distributions.[6]. Many algorithms have been proposed to address the non-Gaussian problem. They can be roughly divided into recursive and batch approaches. The recursive approach is an online implementation of tracking , such as Masreliez filter, multiple modeling (MM) approach, suboptimal approach, and sequential Monte Carlo (SMC) method. The batch approach is an offline implementation that estimates the system state using all measurement data. In general the batch approach is more accurate and the tradeoff is a heavier computation load. The Masreliez filter employs a "score function" to address the non-Gaussian problem. The score function is customized for noise statistics and has to be redesigned for different applications. Therefore, this approach has a heavy computation load. The MM approach, which represents a non-Gaussian system by a mixture of parallel Gaussianly distributed models, is studied in. The posterior probability density function (pdf) of state is modeled by a sum of Gaussians. Various filters are used for model-conditioned state estimation. For example, the Gaussian sum filter (GSF) is given in. The main shortcoming of the MM approach is the number of mode-conditioned filter increases exponentially. Suboptimal methods for model order reduction based on merging and pruning are developed in. One of the popular techniques of this approach is interacting MM (IMM), which is a recursive hybrid filtering method that gives suboptimal state estimates with an advantage of good balance between performance and complexity. In the glint noise is approximated by Gaussian mixture model (GMM) with two components. An IMM approach is proposed to target tracking with glint noise, by transforming the glint noise into two separated models. The SMC approach is another class of filter algorithms. The sequential importance sampling (SIS) algorithm is a Monte Carlo (MC) method that forms the basis for most SMC filters. A particle filtering (PF) is the typical instance of this approach. Recently, the Gaussian mixture Kalman filter was derived for the linear non-Gaussian problem .

The main idea of the GMKF is that any pdf can be closely approximated by a mixture of a finite number of Gaussian. It is shown that the GMKF outperforms the PF and IMM in linear non-Gaussian problems. The statistics of the non-Gaussian noise should be known in advance of sampling in all these above recursive approaches. However, the states and parameters can be estimated simultaneously in the batch approach. The expectation-maximization (EM) algorithm is an iterative procedure for maximum likelihood parameter estimation from measurement data with missing or hidden variables. In the E-step the conditional expectation of state is evaluated. The parameters are estimated for the next iteration in the M-step. In evaluation of the conditional mean and covariance of states in the linear dynamic system case can be obtained by the conventional Kalman filtering technique. In [15] the estimation of state space model in non-Gaussian noise is addressed by the EM-IMM method. The non-Gaussian noise is modeled by GMM. In the E-step the IMM is employed to obtain the suboptimal conditional mean and the covariance of the system states, and the parameters of GMM noise are updated in the M-step.[7]

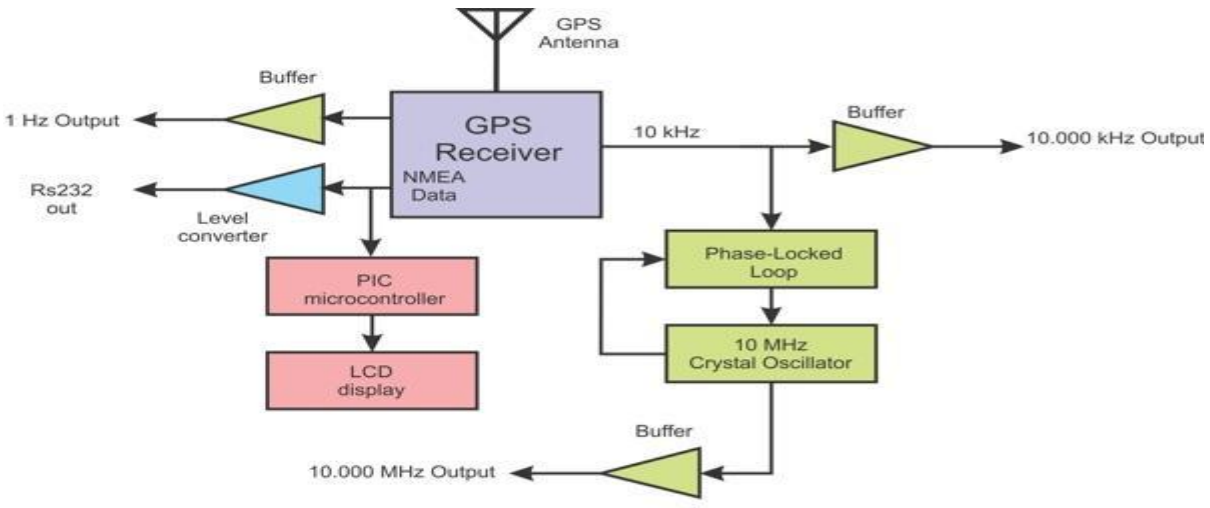


Fig 1: Example of a Block Diagram of GPS

## II. Related Work

### *A. Measurement updating using the U-D factorization.*

The discrete linear filtering problem is treated by factoring the filter error covariance matrix as $P = UDU^T$. Efficient and stable measurement updating recursions are developed for the unit upper triangular factor, $U$, and the diagonal factor, $D$. This paper treats only the parameter estimation problem; effects of mapping, inclusion of process noise and other aspects of filtering are treated in separate publications. The algorithm is simple and, except for the fact that square roots are *not* involved, can be likened to square root filtering. Like the square root filter our algorithm guarantees no negativity of the computed covariance matrix. As is the case with the Kalman filter, our algorithm is well suited for use in real time. Attributes of our factorization update include: efficient one point at a time processing that requires little more computation than does the optimal but numerically unstable conventional Kalman measurement update algorithm; stability that compares with the square root filter and the variable dimension flexibility that is enjoyed by the square root information filter.

### *B. Fast occluded object tracking by a robust appearance filter*

We propose a new method for object tracking in image sequences using template matching. To update the template, appearance features are smoothed temporally by robust Kalman filters, one to each pixel. The resistance of the resulting template to partial occlusions enables the accurate detection and handling of more severe occlusions. Abrupt changes of lighting conditions can also be handled, especially when photometric invariant color features are used, The method has only a few parameters and is computationally fast enough to track objects in real time.

## III. Issue in GPS

We probably wouldn't trust an old map you unearthed from the trunk of our car to help plot the most accurate route, so why haven't we updated the maps on our GPS device? We'll never get from Point A to Point B with inaccurate or outdated information. Each year, we can expect roads to change as much as 40 percent -- that's new roads, closed roads, lane changes, you name it. Think about new developments in our own town -- construction may go on for months or years until one day the roads suddenly open. Eventually those new roads will make it into the next version of digital mapping software, but it isn't instantaneous. How does it happen? The major mapping and navigation companies use a combination of on-the-ground technology (employees driving around and collecting data), user feedback and a variety of other sources to build maps that reflect the reality of the road systems around the world. In a study by the Navigations Systems Research Foundation, it was discovered that some important information is sometimes overlooked by GPS systems, such as types of roads. This is important information to have if your bus has accidentally been routed through a residential neighborhood or your car has been detoured to an unpaved road. While the map data is at fault for inaccuracies, users are usually at fault for outdated data. Many handheld or stand-alone devices can be updated for free by connecting them or the removable media card directly to a computer and downloading new, updated maps from the digital map provider. With frequent downloads, your GPS device will have the most current routing information. Even with the most up-to-date mapping and navigation software, your GPS device is still at the mercy of its satellite network. Accuracy problems can arise from a variety of conditions, from atmospheric to terrestrial. When a satellite isn't able to transmit its position, a situation called an ephemeris or orbital error, it isn't able to establish a link with your GPS device. Atmospheric conditions, specifically in the ionosphere and troposphere, including variations in plasma activity, temperature, pressure and humidity, can cause calculation and accuracy errors in the satellite network. Bad satellite signals and signal interference are some of the most common glitches and happen when something gets in the line of sight between your GPS device and the satellite network. Without a clear and strong signal, your device can't accurately establish your location. Tall buildings, dense foliage, mountains and even reflective objects can cause such a problem. To be sure you always get from Point A to Point B, update your mapping software by Kalman update Algorithm.[3] Since satellite transmission power is low, certain geographical conditions may cause problems with a GPS receiver's ability to record location data: Terrain signals can become degraded and the receiver system may not provide location information if the view of the sky is severely limited. This situation can occur in deep canyons, or under dense vegetation. Urban Canyons large or tall buildings grouped closely together can cause large multi-path and fading errors that may affect the ability to track offenders. Vehicles signals can be lost when an offender is riding in a car or other enclosed means of transportation if the receiver is not placed near a window within the vehicle. Weather signal strength can become degraded by moisture such as rainfall, fog, or snowfall. Because of these factors, it is difficult to ensure complete or thorough GPS coverage at all times. However, with the ongoing advancements in technology, certain system components and features are now available that improve the equipment capabilities. For example, omni-directional antennas enable tracking devices to pick up GPS coverage in virtually any orientation. Flat patch antennas are not as advanced and must maintain an upright position to receive coverage. Reliable radio frequency (RF) technology, cellular towers and Advanced Forward Link Trilateration (AFLT) can also be paired with GPS to enhance system accuracy.[6]

## IV. Kalman Update

The Kalman filter, also known as Linear Quadratic Estimation (LQE), is an algorithm that uses a series of measurements observed over time, containing noise (random variations) and other inaccuracies, and produces estimates of unknown variables that tend to be more precise than those based on a single measurement alone. More formally, the Kalman filter operates recursively on streams of noisy input data to produce a statistically optimal estimate of the underlying system state. The filter is named for Rudolf (Rudy) E. Kálmán, one of the primary developers of its theory. The Kalman filter has numerous applications in technology. A common application is for guidance, navigation and control of vehicles, particularly aircraft and spacecraft. Furthermore, the Kalman filter is a widely applied concept in time series analysis used in fields such as signal processing and econometrics.

The algorithm works in a two-step process. In the prediction step, the Kalman filter produces estimates of the current state variables, along with their uncertainties. Once the outcome of the next measurement (necessarily corrupted with some amount of error, including random noise) is observed, these estimates are updated using a weighted average, with more weight being given to estimates with higher certainty. Because of the algorithm's recursive nature, it can run in real time using only the present input measurements and the previously calculated state; no additional past information is required. From a theoretical standpoint, the main assumption of the Kalman filter is that the underlying system is a linear dynamical system and that all error terms and measurements have a Gaussian distribution (often a multivariate Gaussian distribution).Extensions and generalizations to the method have also been developed, such as the extended Kalman filter and the unscented Kalman filter which work on nonlinear systems. The underlying model is a Bayesian model similar to a hidden Markov model but where the state space of the latent variables is continuous and where all latent and observed variables have Gaussian distributions.[2][5]

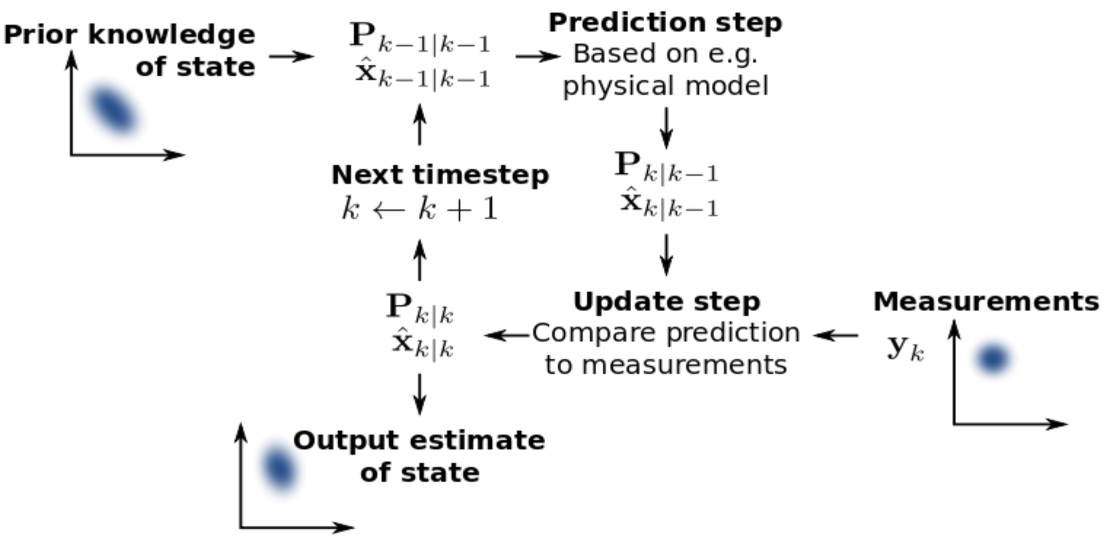


Fig 2: Example of an image of Kalman Update Filter

In order to use the Kalman filter to estimate the internal state of a process given only a sequence of noisy observations, one must model the process in accordance with the framework of the Kalman filter. This means specifying the following matrices: $\mathbf{F}_k$, the state-transition model; $\mathbf{H}_k$, the observation model; $\mathbf{Q}_k$, the covariance of the process noise; $\mathbf{R}_k$, the covariance of the observation noise; and sometimes $\mathbf{B}_k$, the control-input model, for each time-step, $k$, as described below.

This is the model underlying the Kalman filter. Squares represent matrices. Ellipses represent multivariate normal distributions (with the mean and covariance matrix enclosed). Unenclosed values are vectors. In the simple case, the various matrices are constant with time, and thus the subscripts are dropped, but the Kalman filter allows any of them to change each time step. The Kalman filter model assumes the true state at time $k$ is evolved from the state at $(k-1)$ according to where $\mathbf{F}_k$ is the state transition model which is applied to the previous state $\mathbf{x}_{k-1}$; $\mathbf{B}_k$ is the control-input model which is applied to the control vector $\mathbf{u}_k$; $\mathbf{w}_k$ is the process noise which is assumed to be drawn from a zero mean multivariate normal distribution with covariance $\mathbf{Q}_k$. At time $k$ an observation (or measurement) $\mathbf{z}_k$ of the true state $\mathbf{x}_k$ is made according to where $\mathbf{H}_k$ is the observation model which maps the true state space into the observed space and $\mathbf{v}_k$ is the observation noise which is assumed to be zero mean Gaussian white noise with covariance $\mathbf{R}_k$. Many real dynamical systems do not exactly fit this model. In fact, un-modeled dynamics can seriously degrade the filter performance, even when it was supposed to work with unknown stochastic signals as inputs.The reason for this is that the effect of unmodeled dynamics depends on the input, and, therefore, can bring the estimation algorithm to instability (it diverges).

On the other hand, independent white noise signals will not make the algorithm diverge. The problem of separating between measurement noise and un-modeled dynamics is a difficult one and is treated in control theory under the framework of robust control.[2]

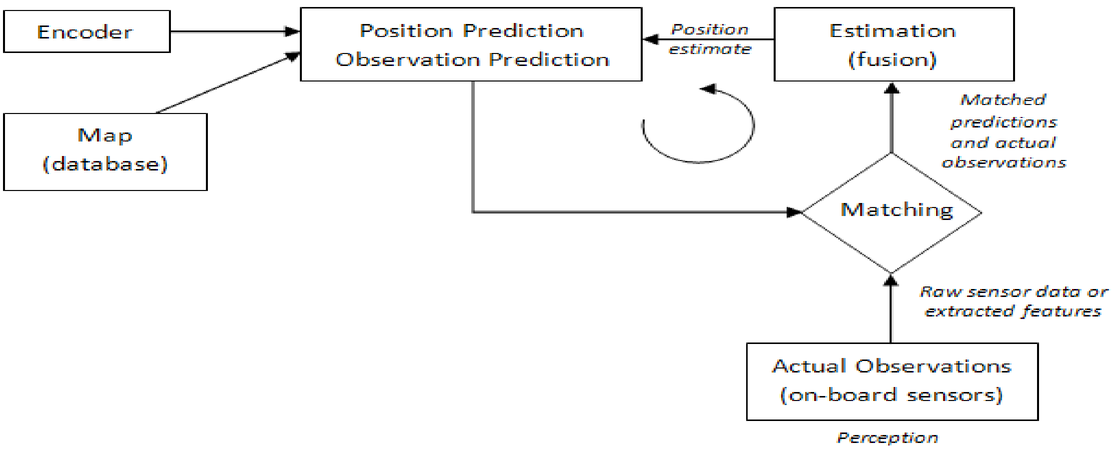


Fig 3:Example of an image of Kalman Flow Diagram

## V. Deriving Equation

### *A. Filtering*

We consider linear time-invariant dynamical systems (LDS) of the following form:

$$x_{t+1} = Ax_t + w_t \quad (1)$$
$$y_t = Cx_t + v_t \quad (2)$$

By the assumptions of the LDS described by (1) and (2), $P(x_t|\{y\}_1^t)$ is a normal distribution.
We seek its mean $x_t^t$ and variance $V_t^t$ .

$$\begin{aligned}\text{Log } P(x_t|\{y\}_1^t) &= \log P(x_t|\{y\}_t^{t-1}, y_t)\\ &= \log P(y_t|x_t, \{ y\}_t^{t-1} + \log P(x_t|\{ y\}_t^{t-1} ) + \ldots\\ &= \log P(y_t|x_t) + \log P(x_t|\{ y\}_t^{t-1} ) + \ldots\\ &= -\tfrac{1}{2}(y_t - Cx_t)' R^{-1}(y_t - Cx_t) - \tfrac{1}{2}(x_t - x_t^{t-1})'(V_t^{t-1})^{-1}(x_t - x_t^{t-1}) + \ldots \quad (3)\end{aligned}$$

Note that, in general, if z is normally-distributed with mean $\mu$ and variance $\sum$,

$$\log P(z) = -\frac{1}{2}(z - \mu)' \sum^{-1}(z - \mu) + \ldots$$
$$= -\frac{1}{2} z' \sum^{-1} z + z' (\sum^{-1}\mu) + \ldots \quad (4)$$

Comparing the _rst terms in (3) and (4) and using the Matrix Inversion Lemma,

$$V_t^t = (C' R^{-1} C + (V_t^{t-1})^{-1})^{-1}$$
$$= V_t^{t-1} - K_t C V_t^{t-1} \quad (5)$$

Where

$$Kt = V_t^{t-1} C' (R + C V_t^{t-1} C')^{-1} \quad (6)$$

To find the time update for the variance, we use the fact that $Ax_{t-1}$ and $wt_{t-1}$ are independent

$$V_t^{t-1} = \mathrm{Var}(Ax_{t-1} | \{y\}_1^{t-1}) + \mathrm{Var}(w_{t-1} | \{y\}_1^{t-1})$$
$$= A V_{t-1}^{t-1} A' + Q \quad (7)$$

Before finding the mean of the normal distribution, we derive the following matrix identity

$$(A + B)^{-1}(A + B) = I$$
$$I - (A + B)^{-1}A = (A + B)^{-1}B$$
$$(I - (A + B)^{-1}A)B)^{-1} = (A + B)^{-1} \quad (8)$$

Comparing the second terms in (3) and (4) and applying the matrix identity (8),

$$x_t^t = V_t^t (C' R^{-1} yt + (V_t^{t-1})^{-1} x_t^{t-1})$$
$$= V_t^{t-1} C'( I - (R + C V_t^{t-1} C')^{-1} C V_t^{t-1} C') + (I - KtC) x_t^{t-1}$$
$$= KtYt + (I - KtC) x_t^{t-1}$$
$$= x_t^{t-1} + Kt(yt - C x_t^{t-1}) \quad (9)$$

The time update for the mean can be found by conditioning on $x^{t-1}$

$$x_t^{t-1} = E x_{t-1} (E(x_t \mid x_{t-1}, \{y\}_1^{t-1}) \mid \{y\}_1^{t-1})$$
$$= E x_{t-1} (A x_{t-1} \mid \{y\}_1^{t-1})$$
$$= A x_{t-1}^{t-1} \quad (10)$$

The recursions start with $x_1^0 = \pi_1$ and $V_1^0 = V_1$.

Equations (5), (6), (7), (9), and (10) together form the Kalman filter forward recursions[8].

*B. Smoothing*

Like the filtered posterior distribution $P(x_t | \{y\}_1^t)$, the smoothed posterior distribution $P(x_t | \{y\}_1^T)$ is also normal. We seek its mean $x_t^T$ and variance$V_t^T$. We are also interested in the covariance of the joint posterior distribution $P(x_{t+1}, x_t | \{y\}_1^T)$

$$\log P(x_{t+1}, x_t | \{y\}_1^T) = \log P(x_{t+1} | x_t, \{y\}_1^T) + \log P(x_{t+1} | \{y\}_1^T)$$
$$= -\frac{1}{2}(x_{t+1} - Ax_t)' Q^{-1}(x_{t+1} - Ax_t) - \frac{1}{2}(x_t - x_t^t)'(V_t^t)^{-1}(x_t - x_t^t)$$
$$+\frac{1}{2}(x_{t+1} - x_{t+1}^t)' (V_{t+1}^t)^{-1}(x_{t+1} - x_{t+1}^t) \ldots$$
$$= -\frac{1}{2} x_{t+1}'(Q^{-1} - (V_{t+1}^t)^{-1} + (V_{t+1}^T)^{-1}) x_{t+1} - \frac{1}{2} x_{t+1}'(-Q^{-1}A) x_t - x_t'(-A'Q^{-1}) x_{t+1}$$
$$= -\frac{1}{2} x_t'(A'Q^{-1} A (V_t^t)^{-1}) x_t + x_t'((V_t^t)^{-1} x_t^t) + \ldots \quad (11)$$

We first simplify these expressions that will appear when inverting (11).

First, using the Matrix Inversion Lemma,

$$S_{22}^{-1} = (A' Q^{-1} A (V_t^t)^{-1})^{-1}$$
$$= V_t^t - V_t^t A' (V_{t+1}^t)^{-1} A V_t^t$$
$$= V_t^t - J_t V_{t+1}^t J_t', \quad (12)$$

Where we define,

$$J_t = V_t^t A (V_{t+1}^t)^{-1} \qquad (13)$$

Secondly,

$$S_{22}^{-1} S_{21} = -(V_t^t - J_t V_{t+1}^t J_t') A' Q^{-1}$$
$$= V_t^t A' ( I - ( Q + A V_t^t A')^{-1} A V_t^t A') Q^{-1}$$
$$= - J_t \qquad (14)$$

Now,

$$V_t^T = S_{22}^{-1} + S_{22}^{-1} S_{21} F_{11}^{-1} S_{12} S_{22}^{-1}$$
$$= (V_t^t - J_t V_{t+1}^t J_t') + (- J_t) V_{t+1}^t (J_t)$$
$$= V_t^t + J_t (V_{t+1}^T - V_{t+1}^t) J_t \qquad (15)$$

And

$$V_{t+1}^T, t = - F_{11}^{-1} S_{12} S_{22}^{-1}$$
$$= V_{t+1}^T J_t$$

Using (5), (12), and (14), this recursion is initialized with

$$V_{T,T-1}^T = V_T^T J_{T-1}'$$
$$= (I - K_T C) V_T^{T-1} J_{T-1}'$$
$$= (I - K_T C) A V_{T-1}^{T-1} \qquad (16)$$

To find the mean, we compare the last terms in (11) and (12). While using (13) , (14) and (15),

$$S_{21} x_{t+1}^T + S_{22} x_t^T = (V_t^t)^{-1} x_t^t$$
$$x_t^T = -S_{22}^{-1} S_{21} x_{t+1}^T + S_{22}^{-1} (V_t^t)^{-1} x_t^t$$
$$= J_t x_{t+1}^T + (I - J_t A) x_t^t$$
$$= x_t^t + J_t (x_{t+1}^T - A x_t^t). \qquad (17)$$

Equations (15), (16) and (17) together form the Kalman smoother backward recursions, equivalently, (16) can be used in the place of (12) and (14) to reduce the computation required to find the covariance [8].

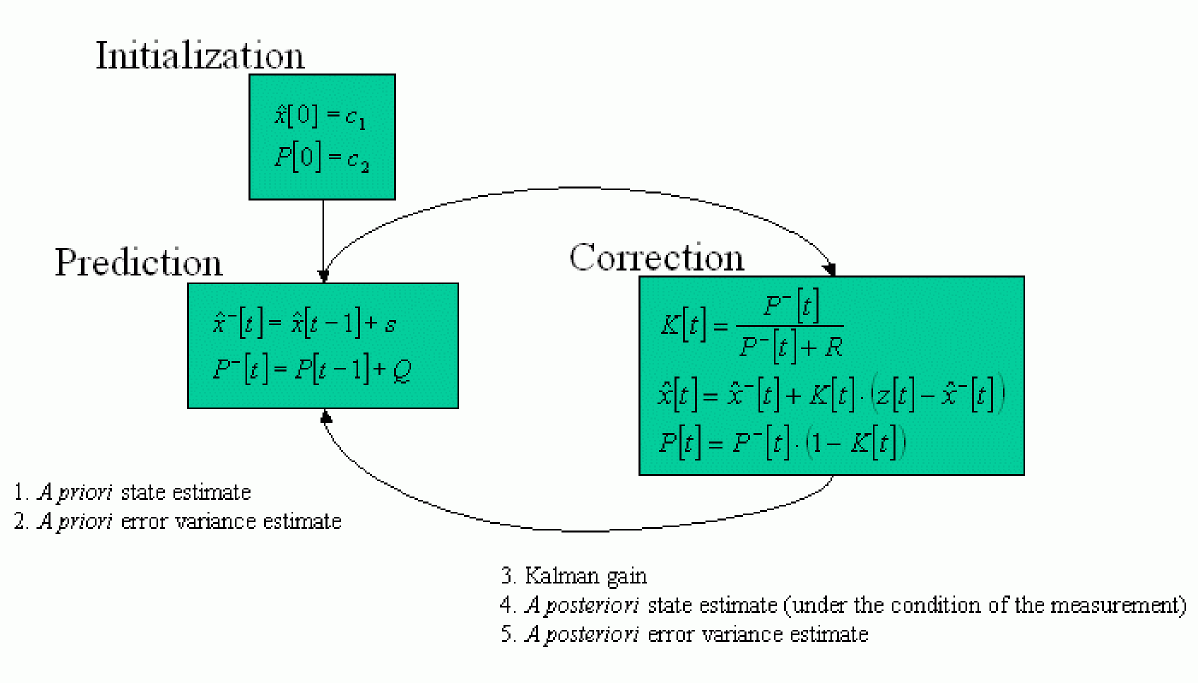


Fig 4: Example of an image of Kalman Schematics

## VI. Advantages

1. Kalman filter is more computationally complicated but it has a more detailed model of the system so it is more accurate in multi-sensor fusion.
2. Whereas the Exponential filter is a simple equation but it is limited by the choice of alpha (Higher alpha => less "memory" of the filter and thus lesser smoothing, but more weightage on measurements whereas lower alpha has higher degree of smoothing but sudden changes are not reflected properly.
3. The Kalman filter is being smart about the noise cancellation. It's a lot smarter than a low pass filter can be because it takes full advantage of all the information stored in the covariance matrix.

## VII. Conclusion

In this article we applied the classical Kalman update and smoothing algorithm to give a precise direction of the location. The result indicates that the prediction gives a very good overall approximation of the direction. We have applied the Kalman update algorithm in our project where the GPS navigation system has been modified. With this algorithm the navigation system has been more precise and accurate. However a trade-off between complexity and efficiency has not been examined.

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