

# GPS data correction using encoders and INS sensors

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## **I. Abstract:**

This contribution introduces the increase of mobile robot positioning based on GPS system using data from other sensors.

Positioning using GPS system is determined, at any time, by measuring the time delay in a radio signal broadcast from several satellites, and using this and the speed of propagation to calculate the distance to the satellites. Position on earth is calculated then by triangulation of intersecting radio signals at the GPS receiver.

Using GPS system for positioning is subject to several sources of errors: ionosphere and troposphere delays, signal multi-path, number of visible satellites, satellite geometry/shading... A typical civilian GPS receiver provides 6-12 meters accuracy, depending on number of satellites available. This accuracy can be reduced to 1m by using a DGPS (Differential GPS) system which employs a second receiver at a fixed location to compute corrections to the GPS satellite measurements.

In order to increase the accuracy of the robot positioning, we use an extended Kalman Filter (EKF) to integrate data from the DGPS system with data from an INS (Inertial Navigation System) and robot encoders. This will allow also kipping robot positioning even if no satellite is visible.

## **II. Introduction**

To reach a reasonable degree of autonomy, two basic requirements are needed: sensing and reasoning. Sensing is provided by an on board sensory system that gather information about the robot itself and the surrounding environment. According to the environment state, the reasoning system must allow the robot to localize itself in the environment and to seek for free paths.

The localization problem can be divided into two sub-tasks: global and local localization. In many applications an initial estimation of the robot pose (position and orientation) is known (supplied directly or indirectly from the user). During the execution of a task, the robot must update this estimate using measurements from its sensors. This is known as local localization [2]. Using only sensors that measure relative movements, the error in the pose estimate increases over time as errors are accumulated. Therefore external sensors are needed to provide information about the absolute pose of the robot. This is achieved by matching the sensors measurements with a model of the environment.

On the other hand, global pose estimation [3,4] is the ability to determine the robot's pose in an a priori or previously learned map, given no other information than that the robot is

somewhere on the map, i.e., it can handle the kidnapped robot problem, in which a robot is kidnapped and carried to some unknown location. Global localization is considerably more difficult than pose tracking because of the data association problem. The level of complexity of this task varies with the size of the environment, but also with the level of symmetry in the environment. It is only by integrating large amounts of data over time that these symmetries can be resolved.

In this application, for its localization, the Robudem robot is equipped with a set of sensors: GPS, inertial navigation system (INS) and wheel encoders. Each of those sensors, when used separately, is subject to a lot of error sources affecting the accuracy of the obtained robot positioning. Our work consists of combining data from those sensors for accurate position estimation. The following gives an overview of the algorithm we proposed for data integration.

### **III. Data integration for robot localization**

In order to increase the accuracy of the robot positioning, we use an Kalman Filter to integrate data from the DGPS system with data from an INS (Inertial Navigation System) and robot encoders. This will allow also kipping robot positioning even if no satellite is visible.

Kalman Filter is an extremely effective and versatile procedure for combining noisy sensor outputs to estimate the state of a system with uncertain dynamics. In GPS/INS/Encoders integration case, noisy sensors include GPS receivers INS and Encoders components, and the system state include the position, velocity, acceleration, attitude, and attitude rate of a vehicle. Uncertain dynamics include unpredictable disturbances of the host vehicle and unpredictable changes in the sensor parameters. Kalman filter optimally estimates position, velocity, and attitude errors, as well as errors in the inertial and GPS measurements.

The relatively low data output rate of GPS receivers (usually 1 Hz) might not meet the cm level accuracy requirements for robot positioning. This problem becomes more serious when the potential temporarily loss of a GPS signal occurs or phase ambiguity resulting from cycle slips considered. INS provides the dynamics of motion between GPS epochs at high temporal resolution and complements the discrete nature of GPS in the occurrence of cycle slips or signal loss.

In addition, positioning with INS requires the integration with respect to time of accelerations and angular rates, the measurement noise accumulates and results in long wavelength errors. GPS errors do not accumulate, but in short term, they are relatively larger and the measurements have poorer resolution.

Integrated systems will provide a system that has superior performance in comparison with either a GPS or an INS system. The main strengths and weakness of INS and DGPS are summarized in the following [1]:

<b>INS</b>	<b>DGPS</b>
high position velocity accuracy over the short term	high position velocity accuracy over the long term
accurate attitude information	noisy attitude information (multiple antenna arrays)
accuracy decreasing with time	uniform accuracy, independent of time
high measurement output rate	low measurement output rate
autonomous	non-autonomous
no signal outages	cycle slip and loss of lock
affected by gravity	not sensitive to gravity

<b>INS/DGPS</b>
high position and velocity accuracy
precise attitude determination
high data rate
navigational output during GPS signal outages
cycle slip detection and correction
gravity vector determination

In case of long temporarily loss of a GPS signal, positioning updating based only on INS system can lead to inaccurate solution. Therefore, a correction using the encoders' data is needed.

#### **IV. Kalman Filtering Modelling**

In our application, a mobile car-like robot "ROBUDEM" travels through the environment using its sensors for localizing itself. A world coordinate frame  $W$  is defined such that its  $X$  and  $Z$  axes lie in the ground plane, and its  $Y$  axis point vertically upwards. The system (ROBUDEM) state vector  $\mathbf{y}_R$  in this case is defined with the 3D position vector  $r = (y_1, y_2, y_3)$  of the gravity center of the robot (supposed in the middle of the axis between the rear wheels) in the world frame coordinates and the robot's orientations roll, pitch and yaw about the  $Z$ ,  $X$ , and  $Y$  axes, respectively  $(\gamma, \theta, \varphi)$ .

$$\mathbf{y}_R = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \gamma \\ \theta \\ \varphi \end{bmatrix}$$

The dynamic model or motion model is the relationship between the robot's paste state,  $\mathbf{y}_R^{t-1}$ , and its current state,  $\mathbf{y}_R^t$ , given a control input  $u^t$

$$\mathbf{y}_R^t = \mathbf{f}(\mathbf{y}_R^{t-1}, u^t, \mathbf{v}^t) \quad (1)$$

Where  $\mathbf{f}$  is a function representing the mobility, kinematics and dynamics of the robot (transition function) and  $\mathbf{v}$  is a random vector describing the unmodelled aspects of the vehicle (process noise such as wheel sleep or odometry error).

The system dynamic model in our case, considering the control  $u$  as identity, is given by:

$$\mathbf{y}_R^t = \begin{bmatrix} y_1^t \\ y_2^t \\ y_3^t \\ \gamma^t \\ \theta^t \\ \varphi^t \end{bmatrix} = \begin{bmatrix} y_1^{t-1} + (\mathbf{v}^{t-1} + \mathbf{V})\cos(\gamma^{t-1})\Delta t \\ y_2^{t-1} + (\mathbf{v}^{t-1} + \mathbf{V})\sin(\gamma^{t-1})\Delta t \\ y_3^{t-1} \\ \gamma^{t-1} + (\omega^{t-1} + \mathbf{\Omega})\Delta t \\ \theta^{t-1} \\ \varphi^{t-1} \end{bmatrix} \quad (2)$$

$\mathbf{v}$  and  $\omega$  are the linear and the angular velocities, respectively.  $\mathbf{V}$  and  $\mathbf{\Omega}$  are the Gaussian distributed perturbations to the camera's linear and angular velocity, respectively.

The GPS satellites transmit two carrier signals on the L-band frequency, a primary signal (L1) at 1575.42 MHz and a secondary signal (L2) at 1227.60 MHz.

The Kalman Filter maintains the state vector  $\mathbf{y}_R$  based on sensors measurements. It also maintains a covariance matrix  $\mathbf{P}$ , which includes the uncertainties in the various states as well as correlations between the states.

At each time step of the filter we obtain the predicted state  $\mathbf{y}_R$  and covariance  $\mathbf{P}$  using the state transition function.

$$\mathbf{y}_R^{t|t-1} = \mathbf{f}(\mathbf{y}_R^{t-1|t-1}, u^t, \mathbf{v}^t)$$

$$\mathbf{P}^{t|t-1} = \mathbf{F}\mathbf{P}^{t-1|t-1}\mathbf{F}^T + \mathbf{Q}^{t-1}$$

where

$$\mathbf{F} = \left. \frac{\partial \mathbf{f}}{\partial \mathbf{y}_R} \right|_{\mathbf{y}_R^{t-1|t-1}}$$

is the Jacobian of  $\mathbf{f}$  with respect to the state vector  $\mathbf{x}$  and  $\mathbf{Q}$  is the process noise covariance.

Considering a constant velocity model for the smooth robot motion:

$$\left. \frac{\partial \mathbf{f}}{\partial \mathbf{y}_R} \right|_{\mathbf{y}_R^{t-1|t-1}} = \begin{bmatrix} 1 & 0 & -\sin(\gamma^{t-1})(\mathbf{v}^{t-1} + \mathbf{V})\Delta t \\ 0 & 1 & \cos(\gamma^{t-1})(\mathbf{v}^{t-1} + \mathbf{V})\Delta t \\ 0 & 0 & 1 \end{bmatrix}$$

The measurement model is needed in the Kalman Filter in order to relate the observation to the unknown parameters. The mathematical models for the GPS L1 and L2 signal are [5]:

$$S_1(t) = A_{1P}P(t)W(t)D(t) \cos(2\pi f_1 t) + A_{1C}C(t)D(t)\sin(2\pi f_1 t)$$

and

$$S_2(t) = A_{2P}P(t)W(t)D(t) \cos(2\pi f_2 t)$$

where

$S_1(t) \& S_2(t)$ :	composite GPS L1 and L2 signal
$A_{1P} \& A_{2P}$ :	amplitudes (power) of in-phase carrier component
$A_{1C}$ :	amplitudes (power) of quadrature carrier component
$D(t)$ :	50bps navigation data stream
$C(t) \& P(t)$ :	C/A code and P (Y) code
$f_1 \& f_2$ :	carrier frequency of L1 and L2

## V. Conclusion

We presented an approach based on Kalman filtering for sensors' data integration for mobile robot localization in a geo-referenced map. The used sensors are Global Positioning System (GPS), Inertial Navigation System (INS) and wheel encoders. Some changes could have been introduced to the used map for localization since it has been established: added/removed objects (cars, containers, trees ...), damaged buildings, in case of aircraft crash... In this case the robot should have the means to rebuild such a map over time.

We are now working on solving this problem by integrating data from a single monocular camera together with the previously used sensors in a Simultaneous Localization and Mapping process. This will allow a more accurate localization of the mobile robot and a reconstruction (mapping) of the environment.

## References

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