Application of System Identification Techniques for Integrated Navigation

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Abstract*—Land vehicle positioning relies mostly on Satellite navigation systems such as the Global Positioning System (GPS). However, GPS signals may be degraded or suffer from a blockage in urban canyons and tunnels, and the positioning information provided is interrupted. To obtain a continuous and reliable positioning solution, GPS is usually augmented with inertial sensors using Kalman Filter (KF). However, low-cost MEMS sensors suffer from complex error characteristics, which are difficult to model by the linearized KF models. System Identification Techniques can be employed to enhance the navigational solution. This paper reviews two algorithms to model and correct the residual and non-linear errors in challenging GPS environments using Parallel Cascade Identification (PCI), a non-linear system identification technique that is cascaded with the Kalman Filter (KF). PCI is first employed to model azimuth errors for a loosely coupled integration. The experimental results demonstrated that the KF performance was significantly improved by augmenting it with PCI to model the linear, non-linear, and other residual azimuth errors. Then PCI technique was employed for modeling residual pseudorange correlated errors to be used by a KF-based tightly coupled RISS/GPS navigational solution. PCI is successfully implemented to provide the non-linear model of pseudorange errors and augmented with tightly coupled KF to provide reliable and accurate positioning solution.

Keywords—* *Land Vehicle Navigation, System Identification, Inertial Sensors, GPS, Kalman Filter, Parallel Cascade Identification

I. Introduction

The field of system identification began by the mid of the twentieth century, and it is highly dependent on its purpose and application [1,2]. It can be used for control strategies or to analyze the properties of a system. System identification is utilized in a variety of applications to address the modeling problems of dynamic systems. The application of system identification technique plays a vital role in deciding that a crude model will be enough, or an accurate model is required for the system dynamics. It is also possible to model the environment of the system to address the application need [3,4]. Linear system identification has played a vital role in the development of modern design methods [3,4,5].

There are several linear system identification methods, such as least-squares identification of a parametric model, repeated least squares, correlated residuals, the maximum likelihood method, Tally principle, and Levin's method. System identification requires the following steps

1. Input/output data measurement with appropriate sampling procedures either in the time domain or in the frequency domain.

2. A set of candidate models and to choose a suitable model structure.

3. An estimation method for minimization of fit between model (predicted) output and measured output.

Mathematical representation of a system's dynamics is termed as modeling. Modeling of the dynamical system is more challenging as the effects of actions take some time to occur. A single system can be described by different models depending upon its applications. A black box approach is based entirely on observed inputs and outputs of the system, as shown in Fig 1. It is widely used for many engineering problems. Using this approach, we can decompose a system into different modules. It is very suitable for linear, time-invariant systems and can also be applied to the non-linear systems.

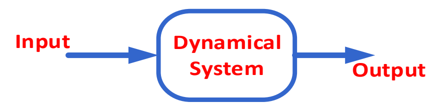


Fig. 1. Illustration of the input/output block diagram of a system

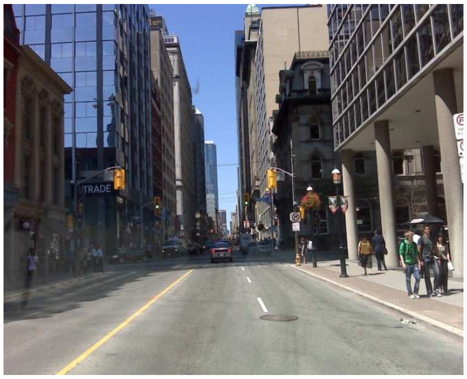
However, linear system identification is not able to address many practical time-varying systems, and it becomes necessary to use non-linear system identification techniques [6,7,8]. The application of non-linear system identification techniques is justified when linear models are not able to handle the excessive non-linear distortion levels. Non-linear system identification techniques include representation of non-linear systems and estimation of a parametric model. For non-linear systems identification, the model selection and parameter estimation are enormously complicated.

This paper reviews the utilization of a non-linear system identification technique called Parallel cascade identification (PCI) to improve the overall navigation solution by modeling errors at the sensor and measurement level.

II. OVERVIEW OF NAVIGATION SYSTEM

The last two decades have seen an increasing trend in the use of Global Navigation Satellite Systems (GNSS) in a variety of positioning and navigation applications. These systems calculate the receiver position by ranging and other information transmitted by visible GNSS satellites using the trilateration principle. GNSS applications include but not limited to passenger cars, taxis, buses, ambulances, police cars, farming vehicles, fire trucks, and mobile robots [9]. Current navigational systems match the position on the digital map with the help of information from GNSS. Therefore, these navigational systems not only identify the current location of a vehicle but also provide route guidance to reach from one location to another. Improved digital maps assist in the enhancement of the navigational systems [9, 10]. Intelligent transport system (ITS) focused on bringing features like collision warning and mitigation, lane-keeping, lane-changing with route guidance to the desired destination, traffic flow guidance, and vulnerable road user detection, driver condition monitoring, and improved vision. These features need navigation systems with higher accuracy, better reliability, availability, and continuity of service [11].

Although the solution provided by GNSS is sufficiently accurate (especially when used in differential mode), it is not able to accomplish the requirements of continuity, reliability, and availability. GNSS may suffer from outages, interference, jamming, and multipath effects in urban canyons, and rural foliage canopies, as shown in Fig 2. So GNSS alone cannot fulfill the requirements of service for modern navigation systems.



Urban Canyon

Under Pass

Fig. 2. GNSS in Challenging Environment

III. PROBLEM STATEMENT

Presently, there is a growing demand for low-cost navigation systems that can provide accurate positioning at all times, even in GPS harsh environments. A full IMU is a self-contained device that consists of three accelerometers and three gyroscopes to continuously measures three orthogonal linear accelerations and three orthogonal angular rates, respectively. These raw measurements are then transformed into position, velocity, and attitude using a sequence of mechanization equations [12, 13]. Other complementary navigation methods rely on information from sensors such as steering encoder, odometer, velocity encoder, and electronic compass. These systems are self-contained and invulnerable to external interference. However, their accuracy deteriorates due to several factors that may include sensor bias, drift, misalignment, and scale factor instability. By integrating these motion sensors with GNSS, a more accurate navigational solution can be obtained [14-16].

Traditionally, integration of GPS with other systems like INS has been provided by KF or Extended KF (EKF), which relies on a linearized error model of both GPS and INS. KF has provided a reliable GPS/INS integration solution for high-end navigational and tactical grades INS. However, KF may not be able to address the complex stochastic and high order errors of MEMS grade sensors. That will result in large values of the non-linear error terms, which are usually ignored during the linearization process while generating the error model for KF. When the low-cost MEMS IMU is integrated with GPS by using traditional KF integration techniques, the solution becomes inconsistent, especially in prolonged GPS outages. For consistent KF results, accurate error models must be available to the KF, but MEMS sensors have composite error characteristics that are difficult to model [12-16].

The main objective of this paper is to enhance the performance of integrated MEMS-based INS/GPS navigation systems through the PCI non-linear modeling approach that can deal with the non-linear parts of INS and GPS errors. In order to achieve this objective, this paper aims at the following: l

1. A thorough review of the PCI algorithm, a non-linear system identification technique with the details of different steps for implementation, is discussed.

2. The research approach in this paper relies on reduced inertial sensor systems (RISS), which limits the reliance on MEMS-based gyroscopes to avoid their high levels of noise and drift rates. The RISS incorporating single-axis gyroscope, vehicle odometer, and accelerometers will be considered for the integration with GPS in one of two schemes. (i) Loosely coupled where GPS position and velocity are used for the integration, or (ii) Tightly coupled where GPS pseudorange and pseudorange rates are utilized.

3. In the first scenario, PCI is employed to enhance the performance of KF by modeling azimuth errors for the RISS/GPS loosely coupled integration scheme. The azimuth non-linear error model is identified online using PCI, and the corrected azimuth is sent to the KF – based RISS/GPS integrated module to improve the overall navigation accuracy.

4. Then PCI is utilize for the modeling of the residual GPS pseudorange correlated errors. This paper provides a brief review to augment a PCI – based model of GPS pseudorange correlated errors to a tightly coupled KF to integrate low-cost MEMS-based RISS and GPS observations.

IV. PARALLEL CASCADE IDENTIFICATION

PCI technique model the non-linear system input/output relation of alternating dynamic linear (L) and static non-linear (N) elements by summing of parallel cascades. The model built has a finite number of parallel LN cascade paths, where each path consists of a dynamic linear element followed by a static nonlinearity. The static nonlinearity can be a polynomial. The model output is the sum of the outputs of the parallel branches, as shown in Fig 3.

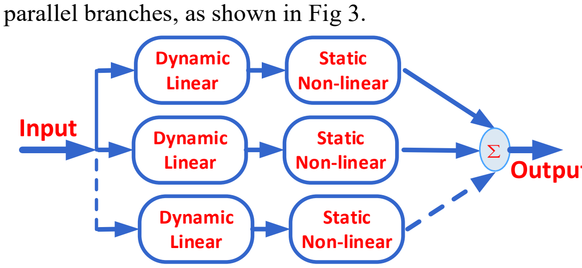
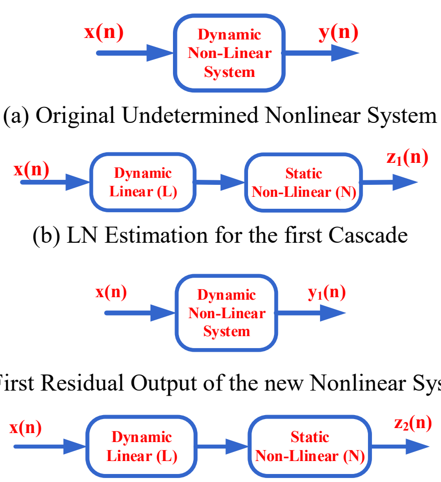


Fig. 3. Illustration of the Parallel Cascade Identification

Frechet in 1910 proved that in continuous time, a finite memory non-linear system whose output is a continuous mapping of its input can be uniformly approximated over a uniformly-bounded equi-continuous set of inputs to an arbitrary degree of precision by a Volterra series of sufficient but finite order [17]. Volterra series represents a functional expansion of a dynamic, non-linear, time-invariant functional. Volterra series is commonly used in system identification. Palm [18] showed that any discrete-time Volterra series with limited memory could be uniformly estimated by a limited sum of parallel LNL cascades, where the static nonlinearities N are exponentials and logarithmic functions. Korenberg [17] showed that any discrete-time finite memory and finite order Volterra series could be accurately represented by a limited sum of LN cascades where the N are polynomials. A major benefit of this technique is its independence of a Gaussian or white input, but identify separate L and N elements and may change depending on the statistical properties of the input chosen [17]. One cascade can be found at a time, and the nonlinearities in the models are localized in static functions. This reduces the computation, as higher-order nonlinearities are approximated using higher degree polynomials in the cascades rather than higher-order kernels in a Volterra series approximation.

The technique begins by estimating the non-linear system by a first such cascade. The difference between the system output and the cascade outputs called residual treated as the output of a new non-linear system. Whereas the second cascade is found to estimate the latter system, and thus the parallel array can be augmented one cascade at a time.

The residual (i.e., the difference between the system output and the cascade outputs) treated as the output of a new non-linear system, a second cascade is found to estimate the latter system, and thus the parallel array can augment one cascade at a time. Having an undetermined dynamic non-linear system with accessible input $x(n)$ and output $y(n)$ (where $n=0,\ldots, T$); T is the length of the data set or record used for the training. One can model it using a parallel cascade supposing that the output can depend on delayed input values $x(n-j)$, for $j=0,\ldots, R$, whereas R is the maximum lag or delay as $(R + 1)$ is the memory length (since the series output $y(n)$ depends on input delays from 0 to R lags or delay). The maximum degree of nonlinearity required for a good approximation of the system is "D". The polynomial degree D cannot exceed T-R since there are $D+1$ coefficients to estimate in the polynomial, and there would be exactly T-$R+1$ points available for the estimation. However, a much smaller value is in practice used for the polynomial degree D, and its value is application dependent. Fig 4 shows the main steps of the PCI algorithm



(a) Original Undetermined Nonlinear System

(b) LN Estimation for the first Cascade

(c) First Residual Output of the new Nonlinear System

(d) Second LN Cascade

Fig. 4. Step-by-Step Implementation of PCI Algorithm

PCI technique can be explained in the following five steps:

1. The first cascade output of the non-linear dynamic system is $z_1(n)$, as shown in Fig 3(b), and it is estimated by a cascade of a dynamic linear (L) followed by a static non-linear (N) element.
2. Then compute the first residual as shown in Fig 3(c),

$$y_1(n) = y(n) - z_1(n)$$

3. Fig 4(d) shows the estimation of the new non-linear system having input $x(n)$ and output $y_1(n)$ by a cascade of L_2 followed by N_2
4. Compute second residual

$$y_2(n) = y_1(n) - z_2(n)$$

5. And so on …

Let $y_k(n)$ be the residual after fitting the k-th cascade, so $y_o(n) = y(n)$. Let $z_k(n)$ be the output of the k-th cascade, so

$$y_k(n) = y_{k-1}(n) - z_k(n) \qquad \text{where } k = 1,2,\ldots\ldots$$

Details of the PCI Algorithm

The salient steps to obtain the impulse response of the dynamic linear element for the current cascade can be listed as

When identifying the k-th cascade, the existing residual before the addition of the k-th cascade is $y_{k-1}(n)$. The approach utilized in this paper to get the impulse response $g_k(j)$, of the linear element L_k of the k-th cascade uses cross-correlations of the input with the current residual, and this impulse response will be one of the following:

a) Impulse response will be input residual cross-correlation

$$g_k(j)=\phi_{xy_{k-1}}(j) = \frac{1}{T-R+1}\sum_{n=R}^{T} y_{k-1}(n)x(n-j) \qquad j=0,\ldots,R$$

A portion of 2nd order cross-correlations of input and residual $\phi_{xxy_{k-1}}(j,A)$ is used : thus the impulse response will be as following $g_k(j)=\phi_{xxy_{k-1}}(j,A)\pm c\delta(j-A)$,

where $\delta(.)$ is the Kronecker delta function, the sign is chosen at random, A is chosen at random from $0,\ldots,R$ and c is chosen such that $c \longrightarrow 0$ as $\overline{y_{k-1}^2(n)} \longrightarrow 0$, e.g. $c = \dfrac{\overline{y_{k-1}^2(n)}}{\overline{y^2(n)}}$ (here the over-bar means the finite-time average from $n=R$ to $n=T$ as in the expression for $\varphi_{xy_{k-1}}(j)$ immediately above)

b) A portion of 3rd order input residual cross-correlation $\phi_{xxxy_{k-1}}(j,A_1,A_2)$ will be used: thus the impulse response will be as following

$$g_k(j)=\phi_{xxxy_{k-1}}(j,A_1,A_2)\pm c_1\delta(j-A_1)\pm c_2\delta(j-A_2)$$

c) We can use this expression up until "n" order cross-correlation using the following

$$g_k(j)=\phi_{x\ldots xy_{k-1}}(j,A_1,\ldots,A_{D-1})\pm c_1\delta(j-A_1)\pm\ldots\pm c_{D-1}\delta(j-A_{D-1})$$

Nevertheless, in practice, cross-correlations up to third order are typically enough.

The output of the linear element calculated by convolution summation is as follows

$$u_k(n) = \sum_{j=0}^{R} g_k(j)x(n-j)$$

Here the linear element's output $u_k(n)$ depends on input values $x(n), x(n-1), \ldots\ldots\ldots\ldots x(j-R)$ and linear element have the memory length of R+1, and $g_k(j)$ is the impulse response of the linear element L_k at beginning the k-th cascade.

To obtain the static non-linear element for the current cascade by polynomial fitting the following steps are followed

First $\overline{u_i^2(n)}$ is calculated, let it equal M, and then the impulse response of the dynamic linear element is adjusted to be $\tilde{g}_i(j) = \dfrac{g_i(j)}{\sqrt{M}}$, to ensure that $\overline{u_i^2(n)} = 1$.

A polynomial (static nonlinearity) is best fit to minimize the mean square error (MSE) of the approximation of the residual. To fit the static nonlinearity, the coefficients a_{id} $(d=0,\ldots D)$ are found to minimize.

$$e_i = \overline{\left(y_{i-1}(n) - \sum_{d=0}^{D} a_{id} u_i^d(n)\right)^2} = \frac{1}{T-R+1} \sum_{n=R}^{T} \left(y_{i-1}(n) - \sum_{d=0}^{D} a_{id} u_i^d(n)\right)^2$$

As noted, the overbar here means a finite-time average.

Minimizing e_i with respect to each of the

polynomial coefficients leads to D+ 1 equations in D+1 unknowns "a_{id}."

$$\overline{y_{i-1}(n) u_i^q(n)} = \sum_{d=0}^{D} a_{id} \overline{u_i^{d+q}(n)} \qquad \text{where} \, q = 0, \ldots, D$$

It is important to know that it is suitable to add the current cascade to the built model or not. The new cascades are to minimize the mean-square error such as to drive the cross-correlations of the input with the residual to zero [17, 19] and given by the following equation:

$$\overline{z_k^2(n)} > \frac{4}{T-R+1} \overline{y_{k-1}^2(n)}$$

Where $\overline{z_k^2(n)}$ denotes the mean square of the candidate cascade's output and $\overline{y_{k-1}^2(n)}$ denotes the mean square of the current residual, i.e., the residual remaining from the cascades already present in the model.

Following are four stopping conditions of building a parallel cascade for the PCI algorithm [19]

1. When a certain number of cascades are added.
2. When a certain number of cascades are analyzed (whether they are included or rejected).
3. When MSE is adequately insignificant.
4. When no residual candidate cascade can reduce the MSE considerably.

V. 2D REDUCED INERTIAL SENSOR SYSTEM

Reduced Inertial Sensor System (RISS) was proposed in [13, 14] involving a single-axis gyroscope and a speed sensor to provide a full 2D positioning solution. The overview of the RISS mechanization can be seen in Fig 5.

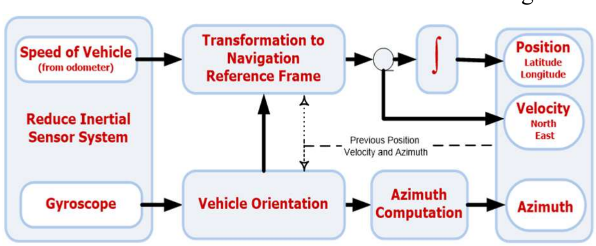


Fig. 5. Block Diagram of 2D-RISS

For RISS mechanization, the azimuth angle is acquired by integrating the gyroscope measurement ω_z. As this measurement includes the component of the earth rotation as well as rotation of the local-level frame on the earth's curvature, these quantities are removed from the measurement before integration [12, 13]. Assuming a relatively small pitch angle for land vehicle applications, the rate of change of the azimuth angle directly in the local-level frame as:

$$\dot{A} = -\left(\omega_z - \omega^e \sin\varphi - \frac{V_e \tan\varphi}{R_N + h}\right)$$

where ω^e is the earth rotation rate, φ is the latitude, v_e is the east velocity of the vehicle, h is the altitude of the vehicle, and R_N is the normal radius of curvature of the earth's ellipsoid.

VI. 3D REDUCED INERTIAL SENSOR SYSTEM

The 2D reduced Inertial Sensor System (RISS) depends on the fact that land vehicles mostly stay on the horizontal plane. Due to the limitation of 2D RISS on roads with slopes especially in hilly and uneven terrain, 3D RISS [14-16] was developed by incorporating two accelerometers for provisioning of pitch and roll angles and incorporating the vertical information in the system model to be used by the RISS/Odometer/GPS integration filter. When pitch and roll are calculated from accelerometers, the first integration of gyroscope to obtain pitch and roll is eliminated; thus, the error in pitch and roll is not proportional to time integration. The outcome of these accurate estimates is superior velocity and position estimates for 3D RISS with odometer, along with upward velocity and altitude that are not calculated before. The overview of the 3D RISS mechanization can be seen in Fig 6.

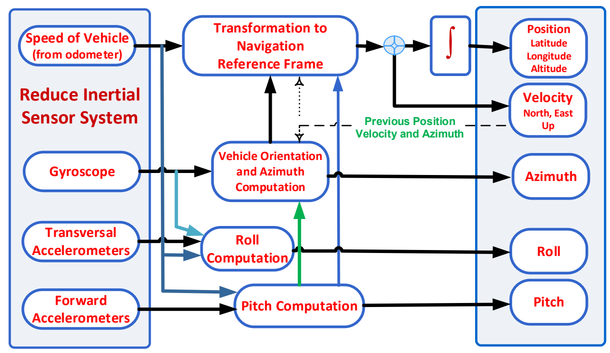


Fig. 6. Block Diagram of 3D-RISS

VII. KALMAN FILTER

Kalman filtering is an optimal estimation tool that provides a sequential recursive algorithm for the optimal least mean-variance (LMV) estimation of the system states [20-21]. The theory of KF is well established, and details can be found in [21-23]. KF is the optimal estimator if the system and measurement models are linear. However, the INS/GPS integration problem has non-linear models. Thus, the linearization of these models is needed, and the filter works with linearized error-state models rather than the total-state non-linear model. The first KF used as for this paper operates in a loosely coupled fashion to fuse the GPS positions and velocities with the 2D-RISS computed position and velocity components. A block diagram of the 2D-RISS and GPS integration is shown in Fig 7.

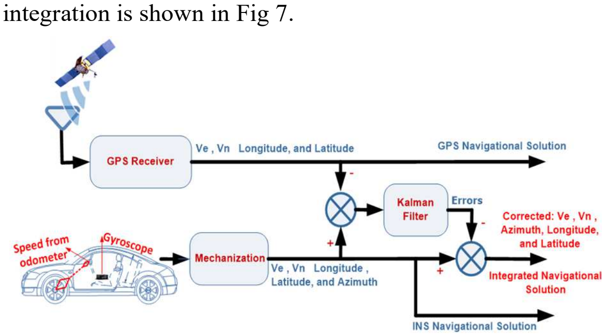


Fig. 7. Schematic Diagram of the Kalman Filter for RISS/GPS Integration

When RISS based loosely coupled integration approach is used, KF fuse the RISS computed position and velocity components with the corresponding GPS positions and velocities. This enables the computation of the positions, velocities, and attitude errors as well as sensor errors. When a GPS outage occurs (i.e., less than four satellites are visible to the receiver with clear line-of-sight), KF will run only the prediction stage of the filter and rely mostly on the error model. While using the low-cost MEMS-based inertial sensors, the application of KF linear error models with stationary White Gaussian Noise for error states estimation can lead to quick deterioration of the navigation solution during GPS outages due to their composite error characteristics.

VIII. PCI FOR MODELING AZIMUTH ERRORS

While using the low-cost MEMS-based inertial sensors, the application of KF linear error models with stationary White Gaussian Noise for error states estimation can lead to quick deterioration of the navigation solution during GPS outages due to their composite error characteristics. For RISS, residual azimuth errors after KF prediction of the linear part of these errors were the principal cause for the deterioration of the solution. PCI, a system identification technique that can be utilized to model the residual azimuth errors, can overcome the limitation of Kalman for RISS/GPS integration and can increase the performance.

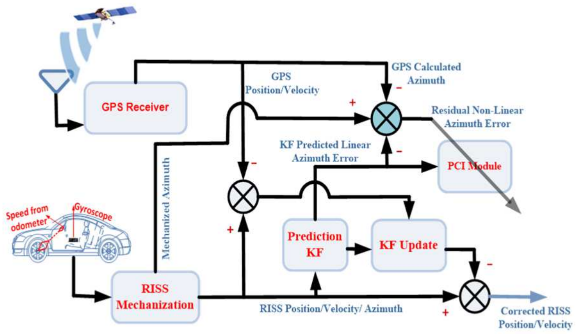


Fig. 8. Loosely Coupled KF-PCI technique during GPS availability

When GPS is available, KF is employed to perform RISS/GPS integration. In parallel, as a background routine, the prediction of KF azimuth is used together with mechanization results and GPS aiding azimuth to derive the true non-linear residual error of azimuth. The block diagram that shows RISS/GPS integration and includes the identification of non-linear azimuth error by PCI is shown in Fig 8. As the training data provides the reference output to construct the azimuth residual non-linear error PCI model. Moreover, the KF sent Azimuth predictions to PCI as the input to build the model. Input and output system dynamics help to identify non-linear errors, and the algorithm can then achieve a residual non-linear azimuth error model.

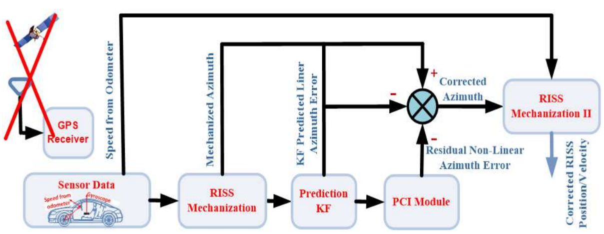


Fig. 9. Loosely Coupled KF-PCI Technique during the GPS outage

Fig. 10. Road Test Trajectory and circles indicate the approximate locations of 60-second GPS outages.

When less than four satellites are visible, GPS outage occurs as a loosely coupled architecture is used. When there is a GPS outage, the identified parallel cascade will be utilized to predict the azimuth errors (residual and non-linear) from the KF prediction for the linear azimuth error. The azimuth angle after correction is passed to new mechanization shown in Fig 9 to calculate the corrected position and velocity.

A road test trajectory using ultra-low-cost ADI IMU and the low-cost Trimble Lassen SQ GPS receiver was conducted in Kingston, ON, Canada, for nearly 35 minutes. The NovAtel ProPak-G2-Plus combines a GPS receiver, and the Honeywell HG1700 IMU via SPAN technology is used as a reference navigation solution. Ten simulated GPS outages of 60-second each were introduced in post-processing for several vehicle dynamic conditions, including high speeds, slow speed, turns, straight portions, and stops, as shown in Fig 10. The errors of KF-PCI and KF-only solutions were compared with respect to the NovAtel reference solution.

The comparison of KF-PCI and KF-only solutions for RISS/GPS integration are presented in Fig 11. The system identification technique PCI, along with KF, was able to model and diminish the residual and non-linear errors in the azimuth and improved the results for ten simulated GPS outages by 69.91%.

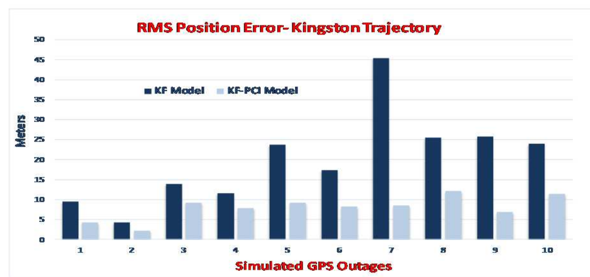


Fig. 11. RMS Position error during GPS outages

IX. PCI FOR ENHANCING KF BASED TIGHTLY-COUPLED NAVIGATION SOLUTION

For loosely coupled integration, clear line-of-sight between the receiver and no less than four satellites is considered a prerequisite to provide position, velocity, and timing aiding. The signals transmitted by the GPS satellites can suffer frequent interference and signal blockage in urban canyons and thick foliage where an uninterrupted clear view of the sky for the receiver is not presumable. Tightly coupled integration using the 3D reduced inertial sensor system is a better choice in challenging GPS scenarios, especially when the number of visible satellites is three or less as it can provide GPS aiding. However, errors of pseudoranges measured by the GPS receiver used as aiding in the RISS/GPS integrated solution will affect the overall positioning accuracy. This section of the paper explores the benefits of using PCI, a system identification technique for modeling residual pseudorange correlated errors that can be utilized by a Kalman filter (KF)-based tightly-coupled RISS/GPS navigational solution.

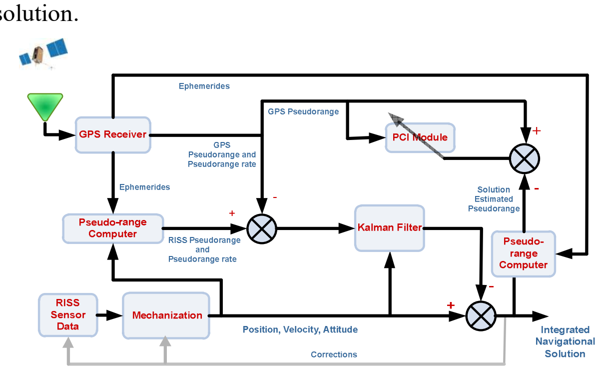


Fig 12: Block Diagram of Nonlinear System Identification to Model the Pseudoranges during GPS Availability using Tightly Coupled KF

PCI can improve the overall navigation solution by modeling residual pseudorange correlated errors to be used by a Kalman filter (KF)-based tightly-coupled RISS/GPS navigational solution, as shown in Fig 12.

When less than 4 satellites are visible, the PCI model for the visible satellites is utilized to estimate the residual pseudorange errors for these satellites, and the corrected pseudorange value is provided to KF, as shown in Fig 13.

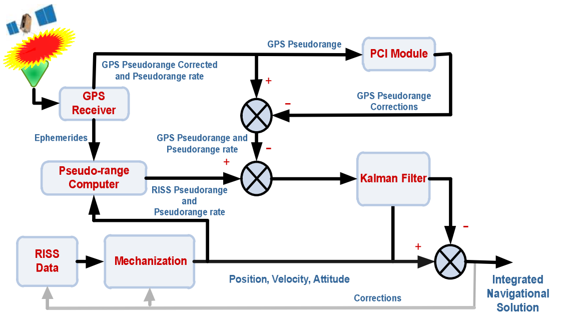


Fig. 13. Tightly Coupled KF-PCI Technique during the GPS outage

A 51 minutes long trajectory was considered to check the validity of the proposed technique. It started at the Royal Military College of Canada, covering the major roads in Kingston city. Six 60 seconds GPS outages were introduced in post-processing during good GPS availability, as shown in Fig 14 on the map as blue circles.

Fig. 14. Road Test Trajectory and circles indicate the approximate locations of 60-second GPS outages.

The trajectory was tested by partial outages having 3, 2 and 1, and 0 visible satellites, respectively. The errors estimated by KF-PCI and KF-only solutions for RISS/GPS integration were evaluated with respect to the NovAtel reference solution. Fig 15 shows the average RMS position errors in meters.

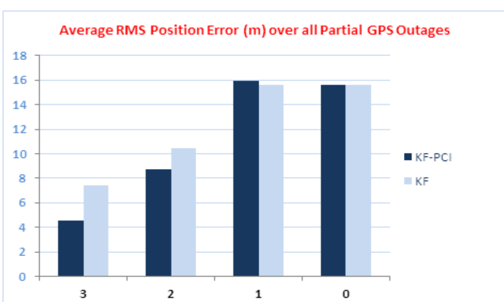


Fig. 15. RMS Position error during GPS outages

The most significant performance of the PCI build model for pseudoranges error corrections was observed when three satellites were available since three corrected ranges served the tightly-coupled solution offering the highest effect. For RMS position errors, the performance enhancement of KF-KF-PCI over KF-only solution os 38.68%. The contributions of pseudoranges error corrections using PCI keep on diminishing for two satellites and one satellite cases. For RMS position errors, the improvement using the proposed PCI model reduced to 16.48% for KF-PCI over KF-only for two satellite cases. There was no improvement using the proposed PCI model for one-satellite cases. No corrections were available for PCI build model for pseudoranges errors in case of zero satellite, and the solution available by KF-PCI and the traditional KF was, in fact equivalent.

X. CONCLUSION

This paper has discussed PCI a non-linear system identification techniques to improve the performance of the integrated RISS/GPS system. Two versions of RISS were used, one based on the single-axis gyroscope, along with an odometer, proposed by the author, integrated with GPS, while the other incorporates two accelerometers to calculate pitch and roll. The complementary strengths of GPS and RISS can be synergized, and optimal performance would be achieved during GPS outages. First, loosely-coupled, and then tightly-coupled integration schemes were considered. Enhancements for both integration techniques were suggested, successfully implemented, and tested for real road trajectories data using KF. Results demonstrated the worth and effectiveness of the proposed system identification techniques for the enhancement of integrating navigation system.

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