e-ISSN 2320 –7876 www.ijfans.org
Vol.10, Iss.3, Mar 2021
  UGC CARE Listed (Group -I) Journal

Inertia Properties of Ground Vehicles Analyzed Via Online Estimation Variables

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Abstract

Handling, stability, and the inclination to roll over are all significantly affected by vehicle factors. This research presents two techniques for real-time estimation of a ground vehicle's inertia values. The uncertain vehicle model provides a probability density function for each of the variables by using the Generalized Polynomial Chaos (gPC) method of prop agating the uncertainties. Many different statistical techniques may be used to these PDFs in order to estimate the parameters' values. Maximum A-Posteriori (MAP) estimation is utilized here. Where is the vector of PDFs of the parameters and z is the observable sensor comparison, the MAP estimate optimizes the distribution of P(|z)? One more approach is to use an adaptive filtering technique. An instance of an adaptive filter is the Kalman Filter. By combining it with the gPC theory, the PDFs of the parameter distributions may be updated at each time step. The filter adjusts the median values of these PDFs so that they are more closely in line with the true values.

Introduction

Inaccurate parameter values are tolerated by vehicle control systems because they are built to be resilient. The act of loading (items) and emptying (fuel, etc.) the vehicle produces these incorrect parameter values. When it comes to most systems, this isn't a big issue, but when it comes to preventing cars from rolling over, it may be disastrous. Because vehicle rollovers are inherently discontinuous occurrences, control systems benefit from more precise parameter readings.

This research is intended to give updates for the on-board systems and estimate these shifts. Several issues should be taken into account. Choosing a suitable data collection strategy is the first step. The second is to choose a model with low data requirements while yet being able to predict the relevant parameters. In this study, we offer two techniques for determining a vehicle's mass and moment of inertia during operation in two dimensions (pitch and roll) without resorting to a terrain profile. We use

Bayesian statistics and a hybrid of the Extended Kalman Filter and the mathematical approach of Generalized Polynomial Chaos to achieve our goals

(gPC). Quantifying the uncertainty in the parameters is made computationally efficient by the Generalized Polynomial Chaos approach [4, 12, 23, 24].

Summarizing the Available Research Estimating parameter values may be done in a variety of ways, each as specific to its area as the techniques themselves. Perhaps the relevant factors are characteristics of electrical devices [11]. Kalman Filtering, Least Squares Error, Lyapunov Stability, Genetic Algorithms, and many more [1, 13, 14, 17, 21] are all viable estimate strategies. The estimation of parameters in vehicle dynamics is no different from the estimation of parameters in other fields [6]. Vehicle mass, inertia, aerodynamic drag coefficient, spring stiffness, suspension damping, and many other factors may all be sources of uncertainty. Numerous techniques are used to calculate an approximate vehicle mass and moment of inertia. To calculate a vehicle's mass, one may use variables such as the engine's torque, the drivetrain's inertia, the wind's resistance, the tires' rolling resistance, and the road's grade [7, 13, 21]. According to [21], this issue arises because the assessment of the vehicle's rolling resistance, a metric that fluctuates non-trivially over time, is particularly sensitive to the estimation of the other parameters. In [17],

we see an example of a technique that may be used to estimate multiple vehicle characteristics. The horizontal center of gravity, mass, and pitch and roll moments of inertia of the vehicle are all determined by the authors of this research. Unfortunately, it is not always the case that the road noise is Gaussian white noise, which is what is needed for this estimate method to work. Errors in the expected parameters might lead to non-trivial estimate errors, which is why a terrain profile is necessary.

e-ISSN 2320 –7876 www.ijfans.org
Vol.10, Iss.3, Mar 2021
  UGC CARE Listed (Group -I) Journal

Mechanics of Moving Vehicles

Vehicle dynamics often use seven-DOF base excitation models like the one shownin Figure 1. The chassis, also called the sprung mass, is what holds the model's suspension components and wheels together (denoted as unsprung masses). The model first utilizes the tire dynamics to get the unsprung masses excited by the terrain profile, and then it uses the suspension components to get the sprung masses excited. The current research eliminates the need for a specific terrain profile, and the model adds the roll degree of freedom in addition to the vertical bounce and pitch degrees of freedom previously studied in [15]. This is crucial because it would be impossible to determine the roll inertia of the vehicle without taking its roll motion into account.

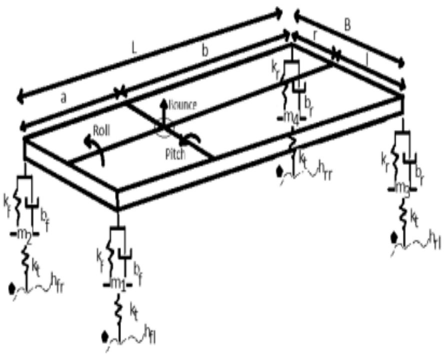
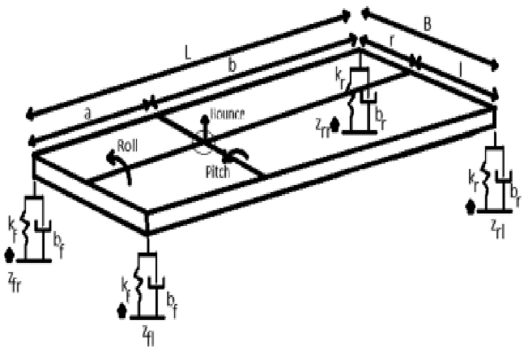


Fig. 1. The seven-DOF vehicle model's dynamics.

The values for the four unsprung masses are denoted by the parameters m1, m2, m3, and m4. For tires, that number is kt, which stands for stiffness. The geometric properties of the sprung mass are described by the parameters a, b, r, l, L, B (where a and b are the distances from the front and rear axles to the center of gravity of the sprung mass, r and l are the corresponding distances from the right and left sides of the vehicle, and L and B are the wheelbase and track, respectively).

transport system). Front and rear wheel damping and stiffness are represented by the parameters kf and bf, respectively. The four vertical acceleration movements of the wheels are used as inputs in the updated model of the seven DOF system. This eliminates the requirement to know the stiffness, weight, and damping of the unsprung masses, as well as the terrain profile, reducing the computational complexity. As seen in Figure 2, this new model allows for the sprung mass to vertically bounce, rotate in the pitch axis, and roll in the yaw axis, for a total of three degrees of freedom.



As shown in Fig. 2, the model's dynamics include three distinct degrees of freedom.

The following assumptions were used in the development of this model: low lateral velocity, low yaw velocity, low longitudinal acceleration, low lateral acceleration, low roll angle, low pitch angle, linear suspension elements, front-and-rear-element symmetry (kfr = kf l = kf), and low angular accelerations and angular rates.

One "center" is used for the sprung mass, while another is used for the collection of unsprung masses. Height, pitch, and roll of the center of mass determine the "center" of the sprung mass. The geometric mean height, zu, cg, roll, u, cg, and pitch, u, cg, for each body is used to define the center of gravity for the unsprung masses in this adaptation of the quarter car model; the centers of gravity for the ensemble of the unsprung masses in vertical bounce, pitch, and roll are thus described as:

$$z_{u,cg} = (L-a)\frac{B-l}{LB}z_{fl} + (L-a)\frac{l}{LB}z_{fr} + a\frac{B-l}{LB}z_{rl} + a\frac{l}{LB}z_{rr} \quad (1)$$

$$\theta_{u,cg} = \frac{\left[-\left(r z_{fl} + l z_{fr}\right) + \left(r z_{rl} + l z_{rr}\right)\right]}{LB} \quad (2)$$

$$\phi_{u,cg} = \frac{\left[\left(b z_{fl} + a z_{rl}\right) - \left(a z_{rr} + b z_{fr}\right)\right]}{LB} \quad (3)$$

Accelerations are measured by ac accelerometers on the instrumented vehicle, therefore similar relations to Equations (1), (2), and (3) may be stated in terms of accelerations. The resulting accelerations are used as inputs in the following three equations: (4), (5), and (6). (6). Wheel vertical displacements are denoted by the parameters zf l, zfr, zrl, and zrr, respectively. The sprung mass's dynamic equations of motion are specified by the following, where Mu, Jpitch, and Jroll are the unknown quantities that represent the sprung mass's mass, pitch inertia, and roll inertia, respectively.

$$M_u \ddot{Z} = \left(\sum_{i=fl,\, fr, rl, rr} F_i\right) - \ddot{z}_{u,cg} \quad (4)$$

$$J_{pitch}\ddot{\theta} = T_{pitch} - J_{pitch}\ddot{\theta}_{u,cg} \quad (5)$$

$$J_{roll}\ddot{\phi} = T_{roll} - J_{roll}\ddot{\phi}_{u,cg} \quad (6)$$

How much the centers of mass of the unsprung and sprung bodies are off from one another in the vertical (Z), pitch (), and roll () directions.

$$Z = z_{s,cg} - z_{u,cg} \quad (7)$$

$$\theta = \theta_{s,cg} - \theta_{u,cg} \quad (8)$$

$$\phi = \phi_{s,cg} - \phi_{u,cg} \quad (9)$$

Using the relative dis placements, the following are the forces and moments acting on the sprung m ass system:

$$F_{fl} = -k_f Z - b_f \dot{Z} + a k_f \theta + a b_f \dot{\theta} - l k_f \phi - l b_f \dot{\phi} \quad (10)$$

$$F_{fr} = -k_f Z - b_f \dot{Z} + a k_f \theta + a b_f \dot{\theta} + r k_f \phi + r b_f \dot{\phi} \quad (11)$$

$$F_{rl} = -k_r Z - b_r \dot{Z} - b k_r \theta - b b_r \dot{\theta} - l k_r \phi - l b_r \dot{\phi} \quad (12)$$

$$F_{rl} = -k_r Z - b_r \dot{Z} - b k_r \theta - b b_r \dot{\theta} + r k_r \phi + r b_r \dot{\phi} \quad (13)$$

$$T_{pitch} = -a\left(F_{fl} + F_{fr}\right) + b(F_{rl} + F_{rr}) \quad (14)$$

$$T_{roll} = -r\left(F_{fr} + F_{rr}\right) + l\left(F_{fl} + F_{rl}\right) \quad (15)$$

Research Methodology

Here, we'll go through the many sensors and other instruments that play a role in achieving this goal. The estimators' mathematical foundations are laid forth here as well.

Collection of Sensor Data

Synthetic sensor data is generated by a seven degrees of freedom car model driving down a simulated route. Using sine and cosine functions with frequencies of 0.77 Hz and 8.3 Hz and magnitudes of 3 cm and 0.3 cm, respectively, and step functions, a synthetic road profile is generated.

Methodology for Estimating Vague Variables

The dynamics of the model describe the parameters to be estimated as having unknown values. Generalized polynomial chaos is used as a mathematical approach to allow the uncertainty in the parameters to be transmitted to the model's dynamics (gPC). Setting initial values for the model's para parameters, as illustrated in Equations (16)– (18), is the starting point.

$$Mass = \overline{mass} + \Delta_{mass} \qquad (16)$$

$$J_{Pitch} = \overline{J_{Pitch}} + \Delta_{J_{Pitch}} \qquad (17)$$

$$J_{Roll} = \overline{J_{Roll}} + \Delta_{J_{Roll}} \qquad (18)$$

Due to the unpredictability of these factors, the answers to the differential equations will likewise be approximate. In gPC, the state space looks like this:

$$\mathbf{x} = \left[\sum_{i=1}^{S} x_1^i \Psi^i(\xi) \;\cdots\; \sum_{i=1}^{S} x_n^i \Psi^i(\xi) \; \sum_{i=1}^{S} v_1^i \Psi^i(\xi) \;\cdots\; \sum_{i=1}^{S} v_n^i \Psi^i(\xi) \right]^T \qquad (19)$$

Parameter values are explicitly added to the state space vector, which means:

$$\mathbf{x} = \left[\sum_{i=1}^{S} x_1^i \Psi^i(\xi) \cdots \sum_{i=1}^{S} x_n^i \Psi^i(\xi) \sum_{i=1}^{S} v_1^i \Psi^i(\xi) \cdots \sum_{i=1}^{S} v_n^i \Psi^i(\xi) \sum_{i=1}^{S} p_1^i \Psi^i(\xi) \cdots \sum_{i=1}^{S} p_d^i \Psi^i(\xi) \right]^T \qquad (20)$$

state variable j, and the i-th term of the power series, denoted by x I j. Similarly, the i-th term in the power series expansion of the j-th velocity variable in the state space is denoted by the notation v I j. When describing the parameters, one uses the notation p I d, where d is the index of the parameter of interest and I is the index of the power series coefficient. The term I () in a gPC series is a tensor product of the basis functions and the random variables used to cover the range of the unknown parameters. The underlying polynomials used as basis functions are orthogonal or orthonormal (such as Legendre Polynomials). See [8, 18, 19, 23, 25] for further specifics. The collocation method is used to determine the coefficients of these power series. In many ways, the collocation method is similar to Monte Carlo simulations; nevertheless, there are two key distinctions. First, we choose certain locations. The collocation matrix then combines the whole set of solutions. We may characterize the collocation matrix as follows:

$$A_{j,i} = \Psi^i\left(\xi_j\right) \qquad (21)$$

where the i-th index represents the basis functions' tensor project and the j-th index represents the points selected from the collocation points. The vectors representing the collocation points are as follows:

$$\xi^j = \left[\xi_1^j \ldots \xi_d^j\right] \qquad (22)$$

Where j is the row of points, in the range (1, j)S, and d is the index of the points picked for each unsure parameter. In most cases, 3S Q 4S collocations are necessary for a stable solution [5]. This leads to the following solution for the coefficients:

$$x^j(T) = \sum_{i=1}^{Q} (A^{\#})_{j,i} X^i(T) \qquad (23)$$

The Moore-Penrose pseudo-inverse is denoted by A#. Using the i-th row vector of collocation points, we may derive the i-th set of state space parameters from the dynamics, denoted by x I and the j-the set of power series coefficients, denoted by x j.

e-ISSN 2320 –7876 www.ijfans.org
Vol.10, Iss.3, Mar 2021
  UGC CARE Listed (Group -I) Journal

methods of estimation

Section 4.2 demonstrates how the model's dynamics are affected by the uncertainty. Once the system is built, the result is a stochastic solution that does little more than spread the uncertainty about. The following two sections elaborate on the techniques used to make such estimates.

Adaptive Kalman Filtering with a Time Delay

To write out the state space form of a system of differential equations, one may say:

$$\dot{x} = f(\mathbf{x}) + \mathbf{w} \tag{24}$$

Where:

$$\mathbf{x} = [x_1 \ldots x_n, v_1 \ldots v_n]^T \tag{25}$$

And w is the vector of process noise. The system measurement equation is defined as:

$$\mathbf{z} = h(\mathbf{x}) + \mathbf{v} \tag{26}$$

The state vector is a part of an observed solution, represented by the observation matrix h. The sensor noise is denoted by the vector v. Linear systems are ideal for the Kalman Filter. The goal of the Extended Kalman Filter (EKF) is to create a roughly linear system by linearizing the system mechanics. This is achieved by doing a linearization of the system dynamics and evaluation of the observation matrices at each time step, k:

$$F_k = \frac{\delta f(x)}{\delta x}|_{x=x_k} \tag{27}$$

$$H_k = \frac{\delta h(x)}{\delta x}|_{x=x_k} \tag{28}$$

The EKF equation is:

$$\mathbf{x}_k^u = \mathbf{x}_k^f + K_k(\mathbf{z_k} - H_k * \mathbf{x_k}) \tag{29}$$

The system takes the initial forecast (or model solution), x f k , and updates it through the Kalman Update equations, Kk, and the residual, (zk − Hk ∗ xk), to update the state variables, x u k . The Kalman Update equation is defined as:

$$K_k = M_k H_k^T \left(H_k M_k H_k^T + R_k\right)^{-1} \tag{30}$$

The covariance matrices, Mk, and, Pk are thus obtained as:

$$M_k = \Phi_k P_{k-1} \Phi_k + Q_k \tag{31}$$

$$P_k = (I - K_k H_k) M_k \tag{32}$$

he system covariance matrix, Mk, is created through the functional matrix, Φk, and the forecasted system covariance, Pk−1. The Rk matrix is the measurement noise matrix, defined as:

$$R_k = E(\mathbf{v}\mathbf{v}^T) \qquad (33)$$

E is the mathematical expectation operator. Qk is the matrix that describes the discrete process noise matrix, through the process noise matrix, Q.

$$\mathbf{\Phi_k} = \mathbf{e}^{F_k T_s} \qquad (34)$$

$$Q = E(\mathbf{w}\mathbf{w}^T) \qquad (35)$$

$$\mathbf{Q}_k = \int_0^{T_s} \mathbf{\Phi_k\, Q\, \Phi_k\, dt} \qquad (36)$$

More explicit detailing and implementation of the EKF can be found in [10, 22, 26].

The Generalized Polynomial Chaos – Extended Kalman Filter

The EKF equations are modified to accept the gPC power series solutions of the state variables. The gPC method calculates the covariances of the variables through multiplication of the power series coefficients as defined by Equation (37), for normalized basis functions:

$$cov\left(x_{d,k}, x_{j,k}\right) = \sum_{i=2}^{Q} x_{d,k}^{i}\, x_{j,k}^{i} \qquad (37)$$

For gPC-EKF the Kalman Update equation is defined as:

$$\mathbf{x}_k^{u,i} = \mathbf{x}_k^{f,i} + K_k\left(\mathbf{z}_k \delta(i-1) - H_k \mathbf{x}_k^{f,i}\right) \qquad (38)$$

$$K_k = cov\left(\mathbf{x}_k^{\mathbf{f}}, \mathbf{p}_k\right) H_k^T \left(R_k + H_k cov(\mathbf{x}_{1\ldots 2n}, \mathbf{x}_{1\ldots 2n}) H_k^T\right)^{-1} \qquad (39)$$

More explicit derivation of this equation can be found in reference [3]. The indexes are defined as: The subscript k indexes time. The u and f superscripts denote the updated and forecasted state space vectors. The superscript i indexes the term of the power series. The 1 . . . 2n subscript denotes that only the state variables, and not the parameters are to be used here. T is the matrix transpose operator. The variables are defined as: z is the vector of the sensor signals. R is the sensor signal noise matrix δ is the dirac delta function H is the linearized observation matrix p is the vector of parameters.

Bayesian Statistics

Parameter values may be estimated using Bayesian Statistics. The method relies on the assumption that the discrepancy between the signal and the model follows a normal distribution. Parameter estimation within a Bayesian framework is described as:

$$P[p|\mathbf{z}] = \frac{P[\mathbf{z}|p]\,P[p]}{P[\mathbf{z}]} \qquad (40)$$

If you're only trying to get an idea of something's likely size, you may safely disregard the word P [z] as a constant scaling factor. Because of this, we may simplify Equation (41) to:

$$P[p|\mathbf{z}] \propto P[\mathbf{z}|p]P[p] \quad (41)$$

The posterior density function of parameter values P[p|z] is a statistical measure of how likely it is that a certain parameter value really exists, given the data. The statistical distribution of the signal-to-model mismatch is denoted by the notation P[z|p]. This is defined given a normal distribution as:

$$P[\mathbf{z}|p] = e^{-\frac{1}{2}\sum_{t=T_i}^{T_f}(\mathbf{z}_t - h_t(\mathbf{x}))^T R_t^{-1}(\mathbf{z}_t - h_t(\mathbf{x}))} \quad (42)$$

At each instant t, the signal is represented by the vector z, and the model's output is represented by the vector h. What we mean by Rt here is the signal-to-noise ratio. Prior distribution of parameters, denoted by P[p], is discussed. The vector of states is denoted by x. Because it takes into account prior information about the distributions of the parameters, this is a potent tool inside the Bayesian framework. This is the time period in which the estimator gains knowledge. To determine the probability distribution P p |z, we first gather a series of data spanning the interval [Ti... Tf]. The parameters whose values maximize P p | z are determined via the Maximum Posteriori (MAP) estimate. Distribution for P[p] is taken from the probability density function of P[p], which is then used in the subsequent estimate. It is the values of the random variables,, and not the parameters, p, that are being estimated. This alters the meaning of Equation (29) to be:

$$P[\mathbf{z}|\xi] = e^{-\frac{1}{2}\sum_{t=T_i}^{T_f}(\mathbf{z}_t - h_t(\mathbf{x},\xi))^T R_t^{-1}(\mathbf{z}_t - h_t(\mathbf{x},\xi))} \quad (43)$$

$$P[\xi|\mathbf{z}] \propto P[\mathbf{z}|\xi]P[\xi] \quad (44)$$

The values of the state space variables (positions and velocities) and the parameters (mass, pitch inertia, and roll inertia) are returned by the collocation matrix using the MAP estimate of the random variables from Equation (31).

$$A(\xi_{Est})\mathbf{x}(t,\xi_{Est}) \quad (45)$$

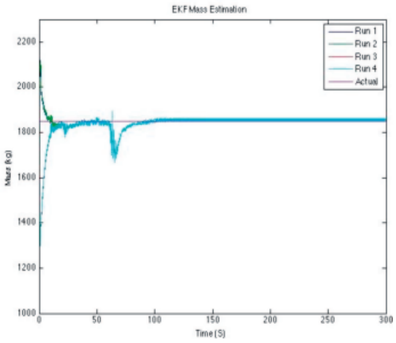
Discussion of Simulated Outcomes

Obtaining Outcomes from an Extended Kalman Filter

The Extended Kalman Filter is used to run four distinct simulations. Parameter estimates for each simulation are shown in figures (3-5), and parameter ranges are included in Table 1. Initial approximations for the parameters are established for the Mass, Pitch Inertia, and Roll Inertia. Mass, pitch inertia, and roll inertia have respective variances of 600 kilograms, 700 kilograms per square meter, and 400 kilograms per square meter.

Table 1. Variations in the parameters used as inputs for the EKF estimation simulations

Run	Mass	Pitch Inertia	Roll Inertia	Poly Order
1	2250	3500	1100	2
2	2250	3500	1100	4
3	1500	2700	600	2
4	1500	2700	600	4



The estimated mass of the EKF as a function of time is shown in Fig. 3.

Specifically, the integrator has a 0.005-second time step. The whole duration is 300 seconds. If the models are a good fit, the EKF estimates are quite accurate. When sensor readings deviate from the assumed range during model generation, the EKF estimations become less consistent. An obvious illustration of this is the change in parameter values that occurs at time t = 61s due to a speed bump. Increasing the polynomial order, changing the sensor noise matrix, adjusting the time step, or a combination of these may all be used to mitigate the impact. Table 2 displays the percentages by which the model parameters deviate from the real during the steady state:

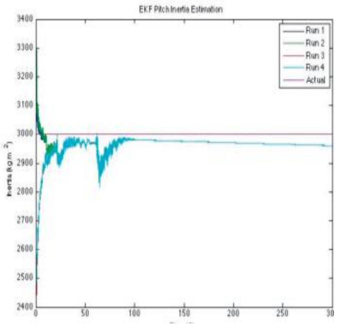


Fig. 4. EKF pitch inertia estimate versus time

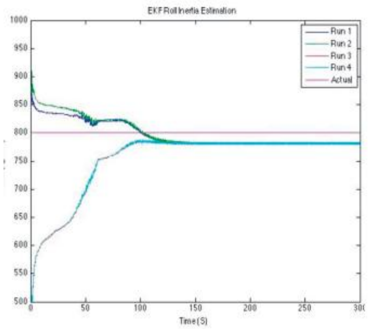


Fig. 5. EKF roll inertia versus time

Table 2. EKF error percentages for final estimation

Mass Error %	Pitch Inertia Error %	Roll Inertia Error %
0.01	-1.31	-2.27

Bayesian Statistics

Eight experiments are detailed below in Tables 3 and 4. For each of the estimation experiments, several of the parameters are changed. These are listed below as the initial estimation of the mass, pitch inertia and roll inertia mean values, the polynomial order (Poly Order) of the gPC expansions, the length of each time interProbability and Statistics with a Bayesian Twist

In Tables 3 and 4, we provide the results of eight separate trials. Several parameters are adjusted in each estimate experiment. Below you'll find the initial estimates of mass, pitch inertia, and roll inertia, the polynomial order (Poly Order) of the gPC expansions, the duration of each time period utilized for estimation, and the total number of estimations.

val used for estimation and the number of estimations performed.

Table 3. Initial parameters fed into the Bayesian MAP estimation algorithm

Run	Mass	Pitch Inertia	Roll Inertia	Poly Order	Time Interval	# of Intervals
1	2250	3500	1000	6	24	1
2	2250	3500	1000	6	1	24
3	2250	3500	1000	4	24	1
4	2250	3500	1000	4	1	24
5	1650	2600	1000	6	24	1
6	2250	3500	1000	4	6	4
7	2250	3500	1000	4	60	1
8	2250	3500	1000	10	24	1

Table 3 details the results of the estimation algorithm. The table details what the final estimates are, and what their percent error is relative to the actual values of the synthetic data model.The estimate algorithm's output is listed in Table 3. In the table, you can see both the final estimates and the percentage error between the estimates and the real values of the simulated data set.

Table 4: The Bayesian Simulation Outcomes

Run	Mass Est	Pitch Est	Roll Est	% Err Mass	% Err Pitch	% Err Roll
1	1905.685	3054.9	785.44	3.01%	1.83%	-1.82%
2	1897.915	3017.19	823.28	2.59%	0.57%	2.91%
3	1934.36	3159	780.08	4.56%	5.3%	-2.49%
4	1852.405	2877	833.44	0.13%	-4.1%	4.18%
5	1914	3069.4	766.7	3.46%	2.31%	-4.17%
6	1897.9	3048.3	858.2	2.59%	2.61%	7.28%
7	1802.5	2876.4	803.4	-1.59%	-4.12%	0.43%
8	1874.2	3047.3	777.7	1.31%	1.58%	-2.78%

Evidence suggests that estimates improve with increasing polynomial order. The mathematics suggests that this conforms to the expected behavior of the gPC. In line with statistical theory, the accuracy of the estimate produced by the Bayesian estimating method improves with the length of the time sequence supplied into it. It is also clear that the guess is more precise the more precise the first estimate is.

Conclusions

In this study, we build a vehicle model that, with only a few sensors and no terrain profile, can estimate the vehicle's mass, pitch inertia, and roll inertia. The methods used provide acceptable results, with the resultant model correlating well with the seven degrees of freedom model. Comparing the Bayesian model to the EKF model, the Bayesian model is more reliable. EKF models may be optimized to run quicker and provide parameter changes in real time.

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