# Mass Flow Meter and Vehicle Information DR Land Vehicles Navigation System in Indoor Environment

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*Abstract* — **Land vehicle navigation has many challenges in some operating environment such as urban canyons and indoor environments (underground parking, and tunnels) where GNSS signals are suffering from multipath or blockage.**

**A Dead Reckoning (DR) land vehicle navigation system is proposed for indoor environments based on a non-conventional navigation sensor which is multiple mass flow meters and the vehicle forward velocity obtained from On-Board Diagnostics II (OBD-II). Two mass flow sensors are placed on the front bumper in a lateral direction of the land vehicle motion direction to estimate the vehicle's heading change in indoor scenarios. A relation between a reference change of heading along with the mass flow sensors data and the land vehicle odometer is estimated through a regression model.**

**Experimental tests have been implemented in underground parking using two mass flow meters of model (SFM3000) and a commercial OBD-II. The results show that the proposed DR system provides a promising navigation solution with an accuracy of 1.58% of the traveled distance for 130 seconds of motion of 443 meters.**

**The proposed DR system opens a new research opportunity using a nontypical sensor that is used for medical applications to be implemented in low-cost land vehicle navigation systems especially with the mass production for such sensors.**

***Keywords— Mass Flow meter, OBD-II, DR, GNSS, INS.***

## I. INTRODUCTION

Recently, Land vehicle navigation using low-cost sensors has attained a lot of research interest all over the globe. Global Navigation Satellite System/Inertial Navigation System (GNSS/INS) integration is the most common navigation system for land vehicle navigation. Unfortunately, GNSS signal suffers from outage [1] in indoor environment and the INS provides the full navigation solution which deteriorates after a short duration due to the large errors of the accelerometers and gyroscopes [2].

There are many techniques to enhance the land vehicle navigation solution in the GNSS denied environment such as aiding the INS with other sensors, enhance the stochastic modeling of the INS[3], and searching for other sensors that have low error drift properties. INS is typically aided by other techniques to mitigate its drift such as land vehicle motion constraints[4] (Non-Holonomic Constraints, Zero Velocity Update, Zero Integrated Heading Ratio), use of map information[5], or use aiding sensors such as Light Detection And Ranging (LiDAR), vision sensors, odometers, magnetometers, barometers, beacon-based aiding sensors or using non-conventional aiding sensors such as ultrasonic sensors[6], Radio Detection And Ranging (RADAR)[7], and Hall magnetic sensor [8] in addition to using the embedded sensors inside the Consumer Portable Devices (CPD) to measure some of the vehicle motion information [9].

However, there are many challenges using these aiding sources regarding the cost and computational efforts. Control sensors of the land vehicles are also used to estimate the forward speed to aid the INS during GNSS signal outage [10].

Mass flow sensors are used in medical and automation applications however some previous researches used such sensors in Unmanned Aerial Vehicles (UAV) navigation by estimating the UAV forward speed to aid the low-cost INS in GNSS denied environment [11].

A UAV integrated navigation system based on IMU, magnetometer, barometer, and mass flow sensors is proposed by [12] where mass flow provides velocity updates along with the Non-Holonomic constraints to the navigation filter to mitigate the INS large errors in indoor environment.

An integrated navigation system is proposed by [13] based on a hall magnetic sensor and mass flow meter for UAV in indoor environment where both the mass flow sensors provide velocity updates to the navigation filter to aid INS to enhance the navigation solution estimation.

This research paper employs a non-conventional sensor in land vehicle navigation where two mass flow sensors are placed on the front bumper of the land vehicle in a lateral direction of the motion to estimate the vehicle's heading change in indoor scenarios.

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## II. METHODOLOGY

A Dead Reckoning (DR) navigation system is proposed using multiple mass flow sensors and land vehicle information where the mass flow meters are used to estimate the land vehicle heading change while the OBD-II provides the land vehicle forward velocity. The proposed navigation system can be applied in indoor environment where GNSS signal is blocked.

### *A. Mass Flow Heading Change Regression Model*

Mass Flow sensors measure the airflow and are typically used in automation, ventilation, environmental control and medical purposes. In this research, the mass flow meter is used as a navigation sensor to form a DR system along with an odometer in indoor environments. Multiple mass flow meters are proposed to be placed on the land vehicle front bumper on the left and the right sides as shown in Fig. 1

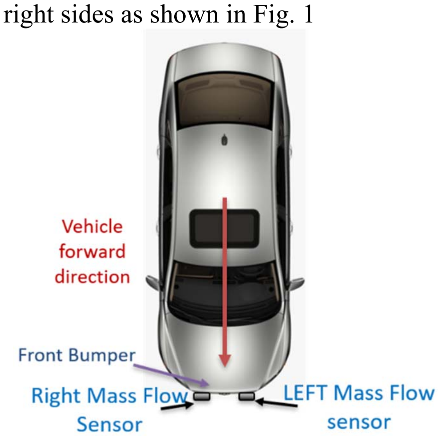


Fig. 1. Mass Flow sensors placement on the land vehicle front bumper

During the straight motion, the mass flow sensors will sense small values of the airflow although they are placed in a perpendicular direction to the dominant airflow.
When the vehicle starts to turn to the right or left, the mass flow sensors measure the dominant airflow due to the turn. Fig. 2 shows the direction of the dominant airflow due to left and right turns.

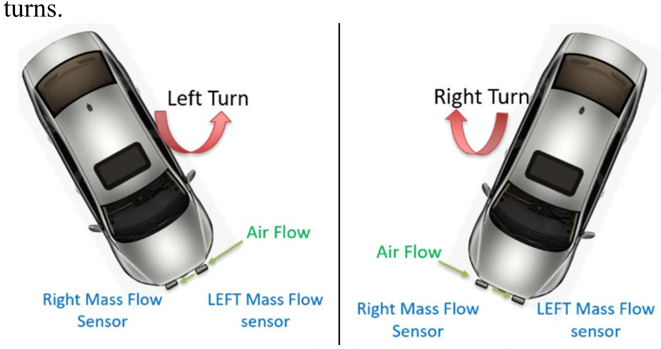


Fig. 2. Mass Flow sensors and airflow during the left and right turns

The land vehicle change of heading is correlated with the right and the left mass flow sensors as well as the forward velocity obtained from OBD-II. This relation is estimated using a reference vehicle heading change through a regression model.

$$Heading\ Change = F(MF_l, MF_r, V_{odo}) \qquad (1)$$

The mass flow change of heading regression model estimation is depicted in Fig. 3

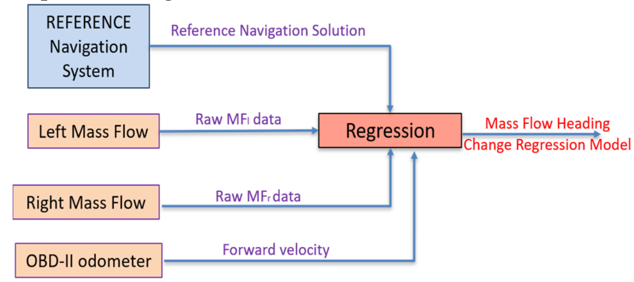


Fig. 3. Mass Flow Heading change regression model estimation using the reference INS and mass flow sensors and OBD-II odometer

In the outdoor environment and during GNSS signal availability, the INS/GNSS provides the land vehicle with the navigation solution. On the other hand, in the indoor environment, the mass flow sensors data along with the OBD-II odometer velocity uses the predetermined mass flow heading change regression model to form a DR system and provides the vehicle navigation solution. The proposed DR navigation system is depicted in Fig. 4.

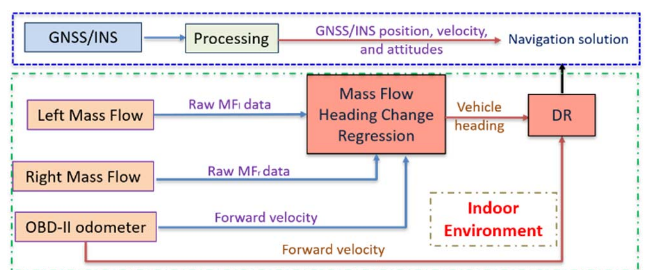


Fig. 4. Proposed integrated navigation scheme based on mass flow sensors and OBD-II odometer

### *B. GNSS/INS Integration Scheme*

The reference navigation solution is GNSS/INS loosely coupled integrated system during GNSS signal availability while in the indoor environment is INS aided with the land vehicle forward speed and Non-Holonomic Constraint with backward smoothing through Extended Kalman Filter (EKF). The error states of the EKF $\delta x$ is defined as follows

$$\delta x_{1\times21} = [\delta P_{1\times3} \quad \delta v_{1\times3} \quad \delta\theta_{1\times3} \quad b_{a_{1\times3}} \quad b_{g_{1\times3}} \quad SF_{a_{1\times3}} \quad SF_{g_{1\times3}}] \qquad (2)$$

Where the first three terms are position, velocity, and attitudes respectively while the last four terms are the biases ($b$) and scale factors ($SF$) respectively for both accelerometers ($a$), and gyroscopes ($g$).
Kalman Filter consists of two main models [14] which are the system model and the observation model where the first model defines the evolution of the states with time while the other describes the measurements [15].
Two stages form the two models which are the prediction and the update stages where the prediction stage is responsible for the system model and the update stage uses the observation model. Equations 3 to equations 8 describe the system model and the prediction stage.

$$\dot{x}(t) = F(t)x(t) + G(t)w(t) \qquad (3)$$

$$x_{k+1} = \phi_{k,k+1} x_k + w_k \quad (4)$$
$$\phi = (I + F\Delta t) \quad (5)$$
$$Q_k = \mathrm{E}(w_k w_k^T) \quad (6)$$
$$x_k^- = \phi_{k,k-1} \hat{x}_{k-1}^+ \quad (7)$$
$$P_k^- = \phi_{k,k-1} P_{k-1}^+ \phi_{k,k-1}^T + Q_{k-1} \quad (8)$$

where $\dot{x}$ is the state vector rate of change of, $F$ is the dynamics matrix, $x$ is the state vector, $G$ is the shaping matrix, and $w$ is the unity variance white noise while $\phi_{k,k+1}$ is the transition matrix.

$I$ is the identity matrix and $\Delta t$ is the discrete-time interval, $P_k$ is the covariance matrix of the states. Finally, the process noise matrix ($Q$) represents the dynamic system model uncertainty.

The observation model and the update stage are described in equations 9 to 13.

$$z_k = H_k x_k + \eta_k \quad (9)$$
$$R_k = \mathrm{E}(\eta_k \eta_k^T) \quad (10)$$
$$K_k = P_k^- H_k^T [H_k P_k^- H_k^T + R_k]^{-1} \quad (11)$$
$$\hat{x}_k^+ = \hat{x}_k^- + K_k [z_k - H_k \hat{x}_k^-] \quad (12)$$
$$P_k^+ = [I - K_k H_k] P_k^- \quad (13)$$

where $z_k$ is the observation vector, $H_k$ is the design matrix and $\eta$ is the measurement noise. The covariance matrix of the measurement noise is $R$ which represents the confidence of the observations. Finally, K is the Kalman gain parameter.

## III. Experimental Results

Real data was collected in underground parking using Pixhawk 4 board which is composed of a GNSS u-blox Neo-M8N receiver and ICM-20689 TDK-Invensense IMU.

Two mass flow meters of model (SFM3000) are mounted on the front bumper of a land vehicle perpendicular to the motion direction as shown in Fig. 5 and 6. An OBD-II interface (Uni-link Mini ELM327 OBD-II Bluetooth Scanner Tool) is used in the experiment to access the regular odometer data.

A reference navigation system was processed using the Pixhawk 4 board through forward and backward smoothing using Extended Kalman Filter (EKF) with the aid of the non-holonomic constraint and the odometer velocity update.

The reference navigation solution is used as a reference during the model regression of the mass flow sensors and also to evaluate the performance of the proposed aiding navigation system.

The experimental results are divided into two main subsections which are: mass flow sensors heading change regression model estimation and the navigation solution results.

Fig. 5. Mass Flow sensors SFM 3000

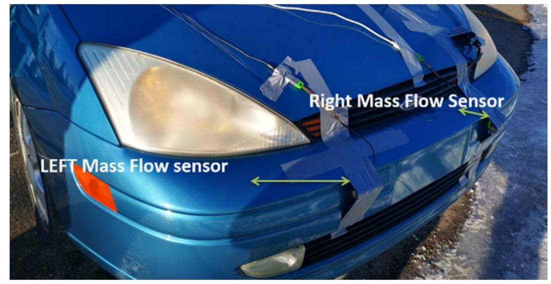


Fig. 6. Multiple Mass Flow sensors installation on the front bumper of a Ford Focus Car

### A. Mass Flow Heading Change Regression Model Results

The regression model is estimated using the multiple mass flow sensors and the odometer data obtained from OBD-II. Fig. 7 and 8 depict the multiple mass flow measurements and forward speed in a dominant sharp left and right turns respectively.

During the land vehicle stop condition, the mass flow sensors do not sense any airflow as the experiment is implemented in underground parking and there is no source of external air.

During the straight motion, the mass flow sensors measurements sense some of the airflow due to the vehicle motion and it is a function of the land vehicle forward velocity i.e. the amount of the airflow that hits the front bumper is large when the land vehicle velocity is high and vice versa. During the sharp left or right turns, the dominant airflow direction is in the same direction of the mass flow sensors and hence they measure more airflow which is a function in both the land vehicle heading change and the forward velocity.

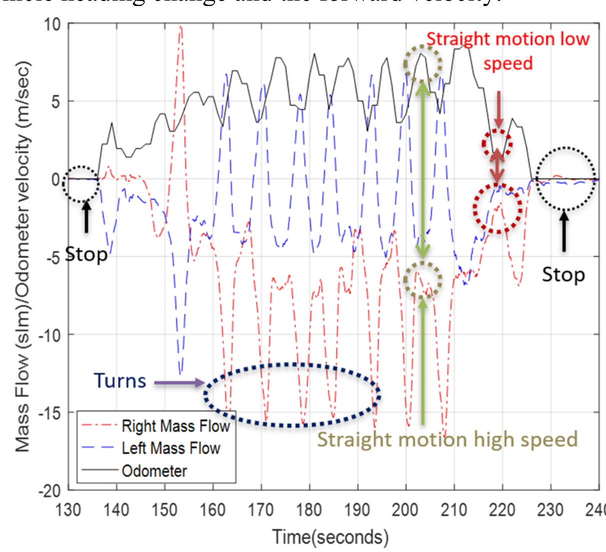


Fig. 7. Multiple Mass Flow sensors and OBD-II odometer data for mostly right turns

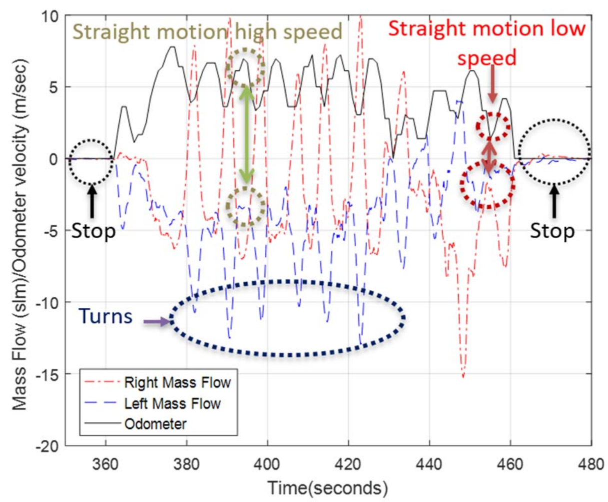


Fig. 8. Multiple Mass Flow sensors and OBD-II odometer data for the mostly left turns

The regression model is created using the mass flow meter sensors and OBD-II forward velocity as shown in Fig. 9, The reference and the estimated heading change using the proposed method and the difference between them are shown in Fig. 10 and 11.

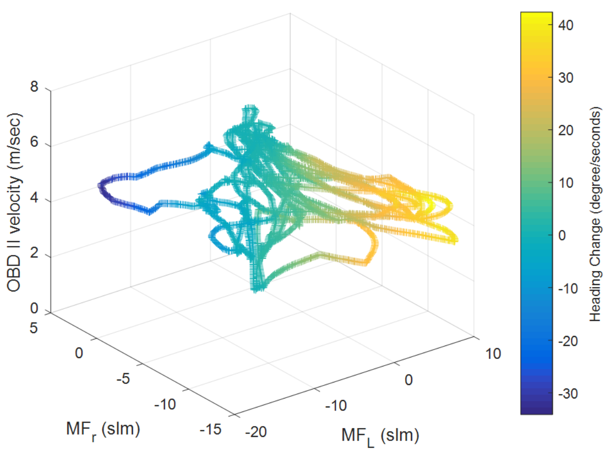


Fig. 9. The used measurements for model regression of the heading change as function of mass flow and OBD-II velocity

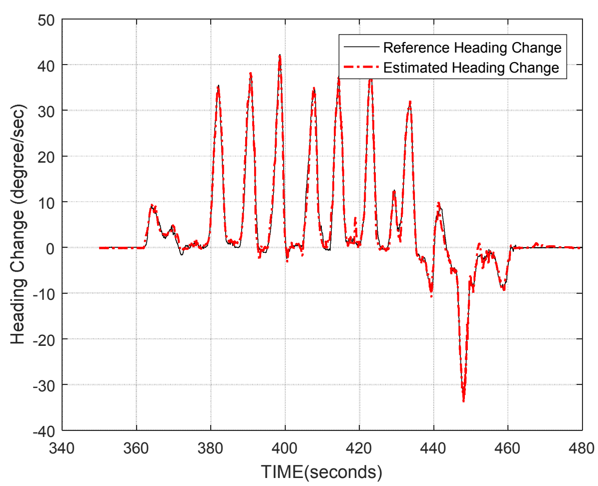


Fig. 10. Land vehicle reference and estimated heading change using the proposed method

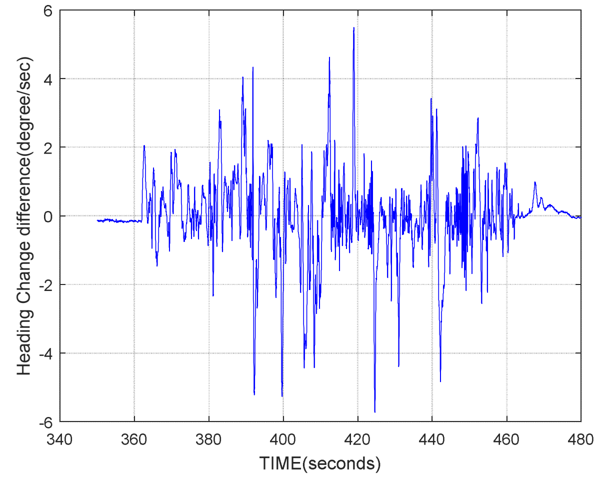


Fig. 11. Land vehicle heading change difference between the reference and the estimated

The Root Mean Square Error (RMSE) is calculated to evaluate the accuracy of the proposed method for estimating the heading change and the RMSE is 1.027 degrees/seconds for 130 seconds.

### *B. Navigation Solution Results*

Two navigation solutions were performed where the first is the proposed calibrated DR based on the mass flow sensors and the OBD-II odometer and the second is a calibrated DR system which is based on the vertical gyroscope to provide a heading change and an odometer. Whole data set of 130 seconds and traveled distance of 443 meters is implemented as an outage instead of multiple short outages.

Fig. 12 depicts the reference trajectory as well as the two DR solutions (the proposed mass flow sensors and the other uses the z-gyroscope).

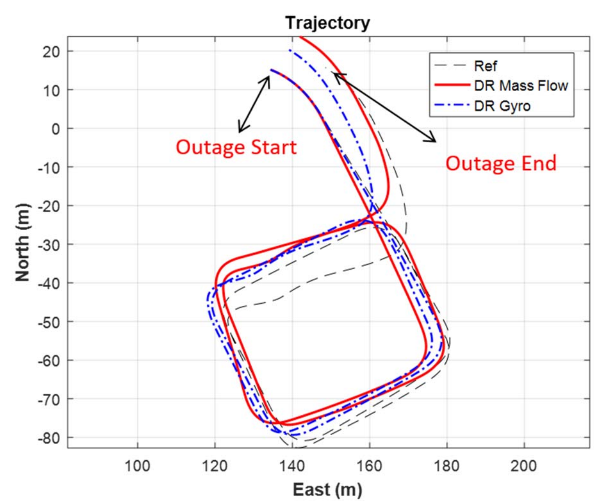


Fig. 12. Reference, DR mass flow, and DR gyroscope trajectories for underground parking

The RMSE for both the DR position is calculated to evaluate the accuracy for each one, the RMSE of the DR which is based on the z gyroscope is 7.180 meters while the position RMSE of the DR based on the mass flow sensor is 7.028 meters for more than 130 seconds.

Navigation results show that the DR navigation system that based on the proposed multiple mass flow sensors along with the OBD-II regular odometer provides slightly accurate navigation states than that provided by the DR based on the z-gyroscope and the OBD-II odometer.

## IV. Conclusion

Dead reckoning land vehicle navigation system is proposed which is based on multiple mass flow sensors and regular odometer velocity obtained from a commercial OBD-II. The mass flow meters are installed on the front land vehicle bumper in a lateral direction to estimate the land vehicle heading change.

A regression model is created using the mass flow sensors data, the OBD-II forward velocity, and the reference heading change. The results show a promising navigation solution with an accuracy of 1.58% of the traveled distance for 130 seconds in underground parking. Future thorough studies are required to investigate the deterministic and stochastic characteristics for the mass flow sensors errors toward employment as a navigation aid.

## Acknowledgment

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