Sensor Fusion For Land Vehicle Localization Using Inertial MEMS and Odometry

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***Abstract*—The paper presents a sensor fusion module based on Error State Kalman Filter (ESKF) for land vehicle localization using inertial MEMS and odometry. The module fuses inputs from the Inertial Measurement Unit (IMU), On-Board Diagnostics (OBD), and GNSS to provide a vehicle trajectory estimate in real-time. Based on multiple field tests the mean circular error was 30 meters after 16 minutes of drive without GNSS signal (or 7 centimeters after 30 seconds) with average speed of 11 meters per second, which was in agreement with a theoretical estimate based on the IMU with 1 °/hr bias instability.**

***Index Terms*—Vehicle localization, autonomous vehicle, global navigation satellite system (GNSS), odometry, inertial sensors.**

I. Introduction

Today the emerging field of autonomous driving demands accurate positioning and trustworthy self-localization methods. The common approach is to fuse all available information sources: GNSS, IMU equipped with the tri-axial gyroscope and accelerometer, odometer, and perception sensors (LIDARs and cameras). The latter provides superior performance (centimeter accuracy) but require powerful graphical processors to perform feature recognition. In contrast to perception sensors, IMUs allow for navigation completely independent of external references (e.g. satellites, road markers, geomaps, databases) and immunity to weather conditions. MEMS IMUs are attractive due to the SWaP-C metric, but only suitable for short-term inertial dead-reckoning because of limited accuracy. In general, the IMU error in the bias estimation of the accelerometer causes error growth which is proportional to the square of operation time, and bias in the gyroscope leads to the error growth proportional to the cube of the operation time [1]. However, when used in conjunction with the odometer, the positional error becomes proportional to the square of time [2]. In this work we demonstrate a real-time sensor fusion module where the gyroscope and accelerometer errors are aided with odometer measurements, GNSS data, and non-holonomic motion constraint. When available, the GNSS is used for position fixing and odometer scale factor correction.

II. System implementation

This section briefly describes the implemented ESKF architecture based on a loosely-coupled integration scheme for vehicle localization. Four basic prediction and correction stages of the ESKF are in the real-time loop:

1) Moving the nominal state of the filter based on the IMU measurements registration.

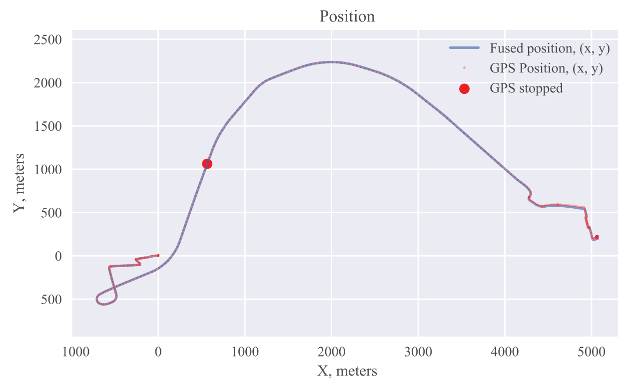

Fig. 1. Restored trajectory from field test #1 (Table I) using IMU+odometer.

2) Observing the error-state using a measurement model.
3) Moving the observed errors back to the nominal state.
4) Resetting the error-state of the filter.

The state vector consists not only of position, velocity, orientation, accelerometer and gyroscope biases, but also includes an odometer scale factor estimate, which was missing in [3].

III. Experimental results

To verify the developed algorithm, a real-time module comprised of a GNSS-receiver, OBD adapter, IMU and Raspberry Pi computer was assembled and mounted on a car. Sampling rates were 100 Hz for IMU data, 1 Hz for odometer and 5 Hz for GNSS data. The off-the-shelf MEMS IMU performance was 0.9 °/hr Bias Instability (BI) and 0.2 °/$\sqrt{\text{hr}}$ Angle Random Walk (ARW). The car was driven on real roads as follows:

1) The filter starts with initially unknown position, velocity, orientation, sensor biases and odometer scale factor.
2) The data from GNSS receiver, odometer and IMU are fed to the filter. The filter observes the errors and starts converging to the most probable output values.
3) At random time, GNSS measurement corrections are switched off in the filter (red circle in Fig. 1 and Fig.3). After that moment, the position is estimated using only inertial and odometer data.

Fig. 1 shows the restored trajectory from one of the trips, see Table I. The overall duration of the trip was 15 minutes, and the GNSS correction was disabled the sixth minute. By that time, the odometer scale estimation had converged to 1.016,

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TABLE I
THE ESTIMATED AND THEORETICAL POSITION ERRORS AFTER GNSS CORRECTION WAS SWITCHED OFF IN THE ESKF FILTER.

#	Time, seconds	Distance, meters	Average speed, meters/second	Experimental position, err., meters		Experimental, angle error, °	Theoretical position error, σ_p, meters
				w. odo	w/o odo		
1	1325	8675	6.6	28.9	27.8	0.9	40.0
2	1159	13503	11.6	32.2	72.3	—	54.2
3	968	9089	9.4	28.3	44.0	1.1	30.9
4	1127	9346	8.3	25.1	61.9	1.3	36.7
5	1047	17230	16.4	60.4	107.4	1.27	62.9
6	783	8572	11.0	20.9	24.5	1.5	24.0
7	458	6051	13.2	13.7	27.9	1.13	10.4
mean±std	981±285	10352±3749	11±3	30±14	52±28	1.2±0.2	37±18

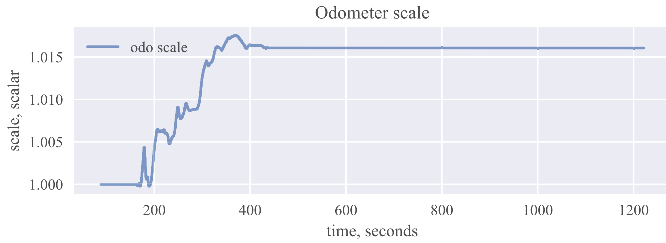

Fig. 2. Odometer scale estimate showing 1.6% difference with GNSS velocity.

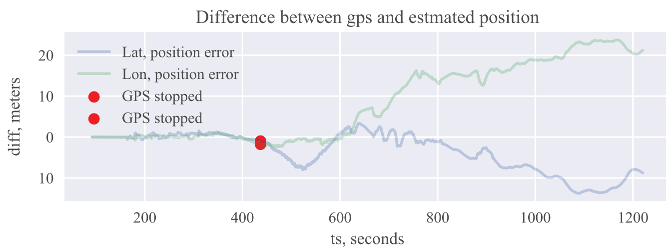

Fig. 3. The difference between GNSS and IMU+odometer solution after GNSS corrections were switched off at time marked with red circle.

revealing a 1.6% difference between the wheel speed sensor and the GNSS velocity, Fig. 2. Without this correction, the position error would have been 16 meters for 1 kilometer traveled. When the GNSS correction is off, the position estimation starts to drift revealing quadratic growth with time for latitude and longitude components, Fig. 3.

Seven trips were made and the results are summarized in Table I. Since each trajectory was different, the standard deviation is meaningless, but the mean values are conclusive. The mean trip duration without GNSS corrections was 16 minutes, the average total distance was 10 kilometers, and the mean speed of a car was 11 meters per second. The mean position and heading angle errors at the end of the track were 30 meters and 1.2 °, respectively. The errors were calculated as an absolute difference between GNSS and IMU+odometer solutions. To check that errors are predominantly from the IMU, the results were compared to a theoretical bound for the position error from BI and ARW values [2]:

$$\sigma_{\mathrm{p}}(t) = v\sqrt{\left(\mathrm{BI}\cdot t^2/(2\sqrt{2\ln(2)/\pi})\right)^2 + \left(2t^{1.5}\cdot \mathrm{ARW}/3\right)^2} \quad (1)$$

where σ_{p} is the standard deviation of the position error as a function of time t, and v is the average speed of the vehicle. The theoretically obtained position error of 37 meters roughly matches with the experimental value of 30 meters (the 20% discrepancy is attributed to insufficient number of trials). Eq. 1 also reveals that for the GNSS signal loss of less than 30 seconds the position error is expected to be 7 centimeters.

Table I shows that without the odometer scale factor correction, the position error was 52 meters. The inclusion of the scale factor into the estimated parameters improved the accuracy of the IMU+odometer solution by 40%, keeping the error within the theoretical bounds. The more accurate an IMU is, the more important is the odometer scale factor correction.

IV. CONCLUSIONS AND FUTURE WORK

A real-time fusion algorithm for GNSS, inertial, and on-board diagnostics measurements was implemented based on ESKF. The proposed approach is cost-effective as it requires only a tactical-grade commercial MEMS IMU paired with an OBD-II adapter for odometer measurements and GNSS receiver (when signal is available). Unlike traditional INS where position error grows cubically in time, the implemented sensor fusion module exhibits quadratic error growth with the odometer aiding. The theoretical prediction of position error from BI and ARW parameters of the IMU and the distance traveled matched the experimental data within 20%. The inclusion of the odometer scale factor into the KF state vector (as an estimated parameter) reduced position error by 40%. The mean circular error after numerous runs without GNSS corrections was 30 meters after 15 minutes (or 7 cm after 30 seconds), which is a solid result for an off-the-shelf MEMS IMU with 0.9 °/hr BI and 0.2 °/$\sqrt{\text{hr}}$ ARW. This work experimentally proves that the stochastic errors is what dominates the position error for a fully factory calibrated IMU.

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