Design and Performance of Wheel-mounted MEMS IMU for Vehicular Navigation

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***Abstract*—In modern cars MEMS gyroscopes and accelerometers provide essential measurements for enhancing the stability and control. Both types of sensors have significant noise at low frequencies, limiting the measurement accuracy especially in low dynamic conditions. In addition, uncompensated accelerometer tilt causes large bias to acceleration estimates. For gyroscopes, physical rotation of the sensor can be used to remove the constant part of the gyro errors and reduce low-frequency noise. In ground vehicles such rotation exists conveniently in wheels. When inertial sensors are attached to wheel, both types of sensors provide information on the rotation, gyroscopes naturally and accelerometers via specific force measurement. In addition, as a result of carouseling, accurate wheel heading, roll and pitch estimation can be estimated with high resolution, and the result is nearly bias-free. Combining the wheel orientation to distance traveled via known radius enables classic dead reckoning mechanization (assuming zero slip) and other vehicle dynamics monitoring systems (considering wheel slip as unknown to be solved). In the paper, we provide details of wheel-mounted inertial system hardware and algorithms and show test results for several system configurations and applications. We discuss future system improvements, in particular, system miniaturization and an energy-harvesting development progress for next-generation inertial systems.**

I. Introduction

Microelectromechanical systems (MEMS) play essential role in automotive electronic control systems, providing measurements for tire pressure monitoring, vehicle stability control, adaptive suspension, rollover protection systems, and navigation systems [1], [2]. While MEMS gyros and accelerometers are suitable for vehicular applications in terms of size and cost, noise properties (large bias and significant 1/f noise) cause problems especially in low dynamic conditions or when measurements are integrated from angular rates to angles or from acceleration to velocity and position [3]. Global Navigation Satellite Systems (GNSS) receivers can be used to complement these measurements but the availability and accuracy drops in urban canyons and underground [4]–[6].

Mitigation of MEMS gyro noise is an actively studied topic, and solutions vary from improving the associated electronics [7] to using external updates [6], [8] and advanced statistical signal processing methods for filtering the gyro noise while retaining the signal [9]–[11]. However, in the absence of external updates it is quite impossible to transform a low-cost MEMS gyro to a high-performance low-noise gyro with signal processing methods alone. This is due to the fact that the 1/f noise heavily overlaps with the useful signal frequency bands, especially when the vehicle dynamics are low. To separate the problematic noise components (bias, 1/f noise) from the signal, methods such as indexing and carouseling have been studied [12]–[18]. Significant improvements in pedestrian dead reckoning obtained using a foot-mounted rotating inertial measurement unit (IMU) have been reported [19], although the test setup was quite complicated form hardware point of view. In contrast, a dedicated rotating system is not necessary if the IMU is mounted at the wheel of a land vehicle [20], [21]. This setup is advantageous as distance traveled can also be deduced from wheel orientation via known radius. Somewhat similar approach is taken in foot-mounted INS wherein zero-velocity update can be applied as measurement whenever foot is on ground. In wheel this kind of velocity update can be done continuously.

For the purpose of revealing the potential of wheel-mounted inertial system, we have designed a wheel-mountable sensor system PI-WINS (Pacific Inertial Wheel Inertial Navigation System) that contains MEMS sensors, battery, Bluetooth module and electronics to run computations and navigation algorithms onboard. It operates in several programmable modes:

1) Computes navigation parameters real-time and sends them via Bluetooth to an onboard computer (can be any other integrated system, data logger or a tablet) 2) Sends real-time raw data to an onboard computer 3) Records hi-rate raw sensor data (up to 2 kHz) to an embedded micro-SD card.

Our onboard computer is a MEMS-array IMU with 48 gyro and accelerometer channels (PI-48), with a BT receiving and sync controller, data storage and WiFi interface. We can now connect up to four PI-WINS units to one onboard computer and have all their data in sync with the in-cabin PI-48 inertial data. All of this data can be used for navigation, wheel dynamics measurements or road quality monitoring applications.

II. Background and Applications

Current research in vehicle automation is heavily focused on improving radionavigation systems and applying modern machine learning techniques for vision-based situational awareness. Systems that rely on external sources of information (GNSS, LiDar, terrestial) are showing attractive results and are a natural direction of research in the age of deep learning. We should not, however, forget the inertial aiding which is always a good back-up in case of external signal outage. Such outages are well know in GNSS use, but vision systems may suffer of similar problems, for example in large open area or during heavy rain. It should be also noted that more precise sensing provides better input to machine learning systems, for example when deciding the correct speed as a function of road condition.

Our system provides valuable measurements right from the vehicle's wheels to the systems mentioned above. The output of the system can be useful in several ways:

1) for positioning computation - this is the primary topic of this paper;
2) for wheel dynamic measurements - hi-rate (2kHz) 6DOF data;
3) for road condition monitoring - direct measurements unaffected by suspension.

An inertial measurement unit attached to a wheel is evidently in a harsh environment. When compared to a cabin fixed IMU conditions like vibration, dirt, moisture, snow, varying temperature due to braking - all need to be taken into account. In addition, requirement for sensor input range is different. But such environmental factors are not that severe when compared to space applications, for instance. Thus, designing and building IP protected, properly temperature compensated unit (-40°...+80°) is not impossible.

For guiding the system design, our primarily targeted markets and applications for this technology have been:

- autonomous vehicles;
- construction and mining machines navigation and safety;
- port logistics and warehouse automation vehicles;
- traction control enhancement.

We have ongoing efforts to design and test an energy-harvester prototype capable of extracting enough energy to power PI-WINS even in slow vehicle speeds. This will make our wheel sensor an "install and forget" solution that goes to sleep when a vehicle is not moving (motion detection) and transmits pre-programmed data messages for an onboard system when motion occurs. Our target design goal is a small unit behind the manufacturers logo on a wheel rim, self-generating enough power to operate, and sending valuable information for in-car safety/navigation systems.

III. Dynamics of Wheel Mounted IMU

We begin by defining wheel-fixed coordinate frame (B) and vehicle chassis frame (V), sharing a common z-axis as

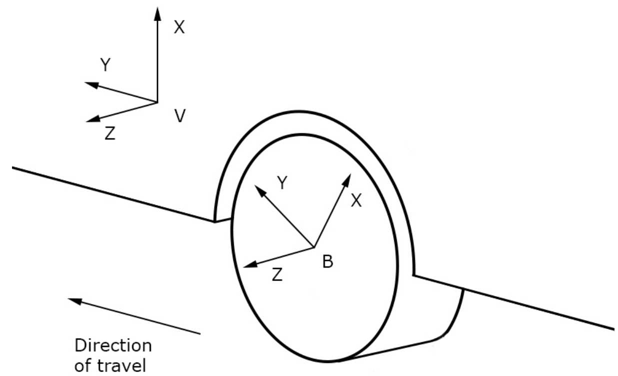

Fig. 1. Axes definitions for wheel-fixed frame (B) and chassis-fixed frame (V)

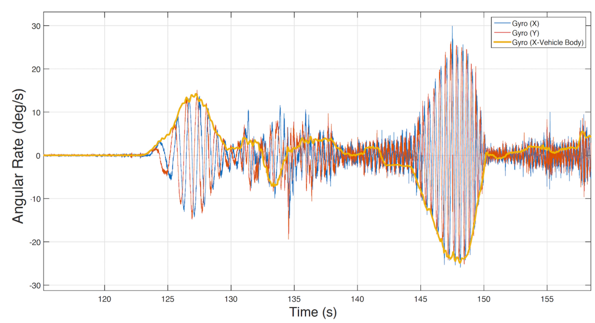

Fig. 2. Heading rate and wheel-mounted gyros

shown in Fig.1. The direction cosine matrix for coordinate transformation can be then expressed as

$$\mathrm{C}_{\mathrm{B}}^{\mathrm{V}} = \begin{bmatrix} \cos(\phi) & -\sin(\phi) & 0 \\ \sin(\phi) & \cos(\phi) & 0 \\ 0 & 0 & 1 \end{bmatrix}, \tag{1}$$

where ϕ denotes wheel phase angle, the amount of rotation from neutral angle where the frames V and B coincide. Vehicle heading rate (ω_H) and roll rate (ω_R) are observed by wheel-mounted IMU as [21]:

$$\begin{aligned} g_x &= \omega_H \cos(\phi) + \omega_R \sin(\phi) \\ g_y &= -\omega_H \sin(\phi) + \omega_R \cos(\phi)\,. \end{aligned} \tag{2}$$

Heading rate from the in-cabin IMU (gyro X) vs. data from two gyros in the PI-WINS on the wheel (g_x and g_y) are shown in Fig.2. As Eq. 2 shows, the gyro data g_y advances the g_x. The direction of turn is not visible in raw data but appears as unbiased heading rate after coordinate transformation.

Assuming the wheel rotates at a constant speed, $\phi(t) = rt$, the constant bias will cancel out and the low-frequency noise significantly decreases [18]. Our tests indicate that the bias cancellation works well even with an accelerating vehicle, as acceleration and biases can be observed with an extended Kalman filter framework.

A. Velocity updates and centripetal acceleration

The required coordinate transformation ($\mathrm{C}_{\mathrm{B}}^{\mathrm{V}}$) should be performed with aid of external angle information that does not suffer from drift; accelerometers are conveniently available for this. The accelerometer triad measures specific force acceleration [22]

$$\mathbf{a}_{\mathrm{SF}}^{\mathrm{B}} = \ddot{\mathbf{p}}^{\mathrm{B}} - \mathbf{g}^{\mathrm{B}}, \tag{3}$$

where $\ddot{\mathbf{p}}^{\mathrm{B}}$ is acceleration in body frame. Assuming it is known or a noise term $\mathbf{n}$ one obtains

$$\begin{aligned} \mathbf{a}_{\mathrm{SF}}^{\mathrm{B}} &= -\mathbf{g}^{\mathrm{B}} + \mathbf{n} \\ &= \mathrm{C}_{\mathrm{L}}^{\mathrm{B}} \begin{bmatrix} -\mathrm{g} \\ 0 \\ 0 \end{bmatrix} + \mathbf{n}. \end{aligned} \tag{4}$$

Furthermore, assuming the locally level L frame coincides with the vehicle frame V

$$\begin{aligned} &\frac{1}{\mathrm{g}}\mathbf{a}_{SF}^{B} = \\ &\left(\mathrm{C}_{\mathrm{B}}^{\mathrm{V}}\right)^{T} \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} + \mathbf{n}, \end{aligned} \tag{5}$$

and thus the first row of $\mathrm{C}_{\mathrm{B}}^{\mathrm{V}}$ in (1) is observable, and phase angle $\phi(t)$ can be estimated. It should be noted that this is just one way to approach the filtering problem in wheel-mounted inertial systems. For example, the wheel contact point can be assumed stationary and zero-velocity observation can be thus added in the filter. In this sense the wheel-mounted inertial system is another example of applying velocity constraints [23], [24], with the extra aid of carouseling effect. The unbiasedness can also improve the centripetal acceleration estimation. Assuming Ackermann steering geometry and zero slip angles, the lateral acceleration can be computed, using [25]

$$a_c = \omega_H \dot{\phi} \mathrm{R} \tag{6}$$

and radius of curvature is

$$r_c = \frac{\dot{\phi}\mathrm{R}}{\omega_H}. \tag{7}$$

If heading rate estimates are averaged over full wheel revolution the gyro bias does not affect the lateral acceleration estimate. The remaining essential errors are due to gyro white noise, inaccuracy in wheel radius R and inaccuracy in $\dot{\phi}$. In wheel-mounted INS the accelerometer errors can be also tackled efficiently when bias, tilt error, and vibration affect the results much less than in the traditional approaches. Coarse estimate for the acceleration error due to angular random walk noise can be obtained by using the Allan deviation specification of the gyro at $\tau = T$, and multiplying it by $\dot{\phi}\mathrm{R}$. For low-cost MEMS gyro with noise density 0.023 $\mathrm{dps}/\sqrt{\mathrm{Hz}}$ [26] and heavy equipment vehicle traveling at 20km/h the resulting error (1σ) would be approximately 0.11 $\mathrm{m/s^2}$.

Fig. 3. Wheel sensor PI-WINS

Fig. 4. PI-WINS on a wheel's rim

IV. Hardware and Data Format

The wheel sensor (PI-WINS) is equipped with the Invensense ICM-20602 sensor. The sensor board is rigidly attached to the PI-WINS enclosure limiting negative resonant effects and proving maximum stability for the sensitivity axes stability. The sensor board is also thermally detached from the enclosure to minimize temperature gradients. After the assembly, PI-WINS is calibrated (axes, biases and scale factors) and temperature compensated from -40°C to +80°C.

The unit uses ARM Cortex-M4 as the main processor. The radio channel is built on Bluetooth technology using Murata chip and BLE (Bluetooth Low Energy) protocol. The built-in Li-pol battery has a capacity of 240 mAh and is enough for powering the PI-WINS for 10-20 hours, depending on the load of BLE transmission (mode of operation). There is also a built-in eMMC 16gB flash memory card for logging hi-rate sensor data (up to 2 kHz) for specific wheel dynamic measurements. The logged hi-rate data is accessible via a mini-USB interface that is IP-68 protected. Current model of PI-WINS is shown in Fig.3. Example of PI-WINS installation on a car rim is shown in Fig.4.

In testing we also used a PI-48 MEMS IMU (that we design

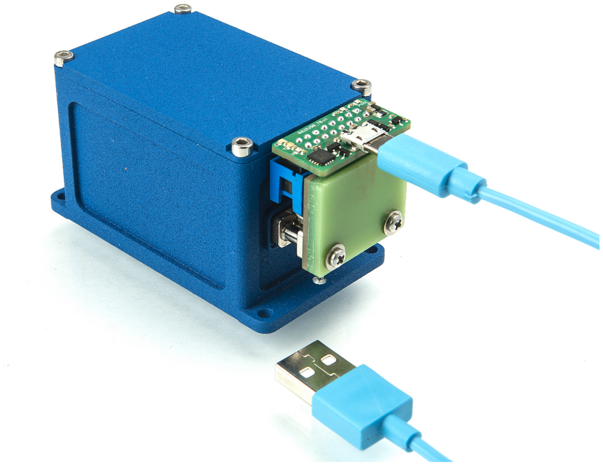

Fig. 5. PI-48 MEMS IMU

and manufacture) with an array of 48 gyros and accelerometers (48xICM-20602). The proper orientation of the sensors in the array not only lowers the noise and improved the bias stability, but also reduces overall temperature coefficient and hysteresis, which, in turn, leads to better units stability after temperature calibration. The unit is IP-67 protected and has several interfaces: RS232, RS485 and CAN2.0. The PI-48 MEMS IMU is shown in Fig.5.

A. Data Format

The wheel sensor PI-WINS, as any other inertial sensor, provides relative navigation solution. PI-WINS provides incremental heading (with respect to some initial value) and incremental distance traveled, measured in wheel rotation counts. It is sufficient information to apply a classic Dead Reckoning (DR) algorithm and compute a 2D navigation solution. The initial heading, wheel diameter and altitude can be estimated with GNSS integration or modern map-matching methods [27]. Currently, PI-WINS operates in 2 modes:

1) Low power mode (real time): all the calculations are made in the sensor and the real-time delta-heading and delta-distance are sent via bluetooth to a dedicated receiver;
2) EKF mode (time lag): raw sensor data is transmitted to an onboard computer where more computationally heavy EKF algorithms are run and better navigation solution is computed.

For the low power mode, the current accuracy specifications for the unit are:

- Output data packet rate: 10 Hz;
- Interface: USB (with BT dongle);
- Wheel rotation rate: up to 10 full revolutions per second (600 rpm);
- Wheel heading angle rate: $<$1000 deg/sec;
- Wheel heading angle error: 1 deg per 1 hour of driving time.

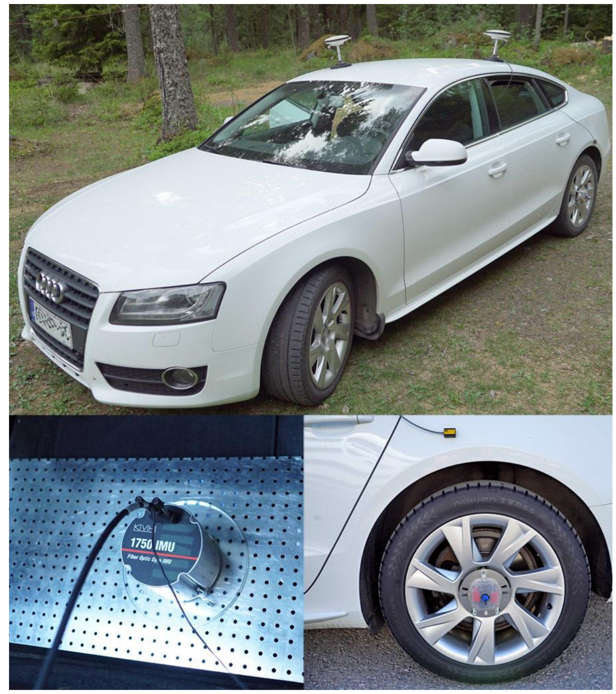

Fig. 6. Test car with some of the equipment

V. Test Results

In the testing we used the following equipment:

- PI-WINS wheel sensor
- PI-48 MEMS-array IMU
- NovAtel SPAN with KVH FOG IMU
- uBlox ZED-F9P Rx

Test vehicle with PI-WINS (and the BT dongle) on the wheel is shown in Fig.6.

As we explained above the most important data from the wheel sensor PI-WINS is the unbiased heading and precise wheel rotation count. Let us first demonstrate how well PI-WINS estimates the vehicle heading compared to SPAN and ZED-F9P solutions. Fig.7 shows the result of a nearly 15 min drive with speeds of up to 25 km/h. After initial heading initialization (with F9P), the max error in heading estimation is around 2.3 deg (RMS).

Fig.8 shows the estimation of vehicle speed by PI-WINS, SPAN and F9P. Here, we used PI-WINS measurements of wheel rotation and the known wheel diameter. The error in speed estimation is 0.23 m/s (RMS).

Fig.9 show the results for this test: 15 min drive, 3.1 km total distance traveled, 20 km/h max speed. For PI-WINS computation the final 2D position error is 23 meters. In comparison, high-accuracy MEMS-array IMU (PI-48) with odometer input has larger error (112 m). It should be noted that for PI-48 result the initial bias was removed in the initialization. This also removes the vertical component of Earth rate. For the PI-WINS, the Earth rate remains in the solution (this is not corrected in the results). We expect the difference to be even larger with filter that is tuned to handle

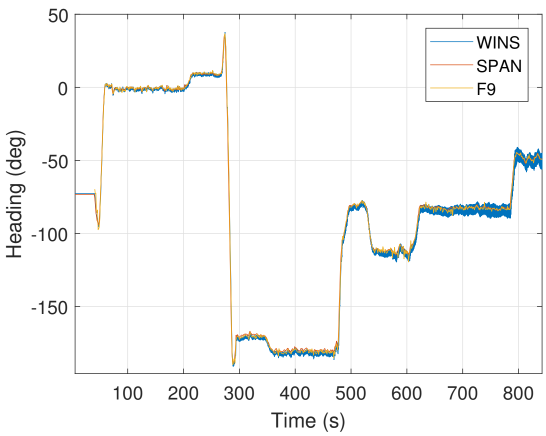

Fig. 7. Heading estimation by PI-WINS, SPAN and ZED-F9P

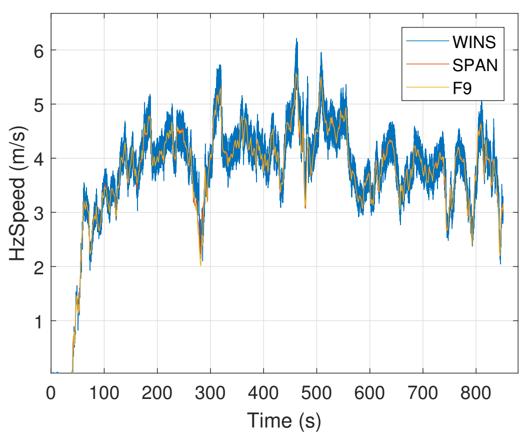

Fig. 8. Speed estimation by PI-WINS, SPAN and ZED-F9P

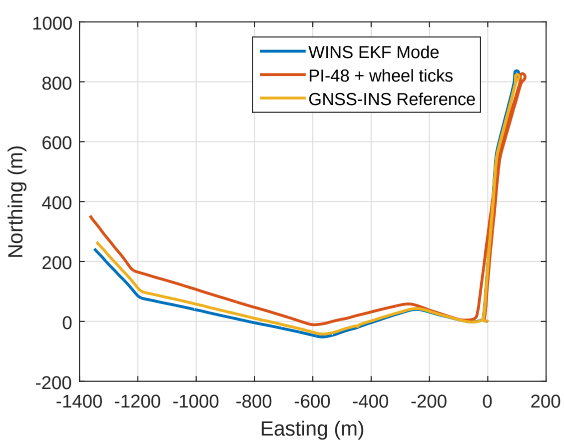

Fig. 9. Comparison of PI-WINS solution vs. in-car AHRS and wheel ticks

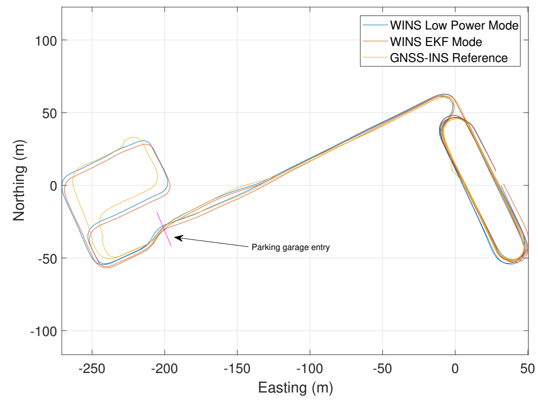

Fig. 10. PI-WINS position estimation

errors distinctive to wheel-mounted INS (modulation of Earth rate and g-sensitvity). In here the progress in low-cost precise GNSS receivers should be mentioned, as it is very relevant to inertial system integration. We have tested new uBlox ZED-F9P module with PI-WINS and results look very promising. For example, the real-time solution of this low-cost receiver was used to estimate the lever arm with standard deviation of only 1.4 cm. Such advances in new low-cost receivers will really change the opportunities of dead reckoning systems in general.

In another shown test, the total driving time is 15 minutes and max speed is 30 km/h. Fig. 10 shows the results for this test - initial heading and position are taken from DGPS solution, the rest is fully inertial 2D navigation solution computed from the PI-WINS wheel data. Here, we show 2 modes of PI-WINS operation - one is a real time computation by the PI-WINS itself (low power mode, PI-WINS transmits via Bluetooth delta-heading and delta-distance traveled at 10Hz) and the other is a more computationally heavy algorithm (EKF) that is run on a computer using raw 2kHz data logged by PI-WINS on its internal storage. The two solutions are really close in this particular case, but in the longer tests EKF solution outperforms the simplified real-time solution. It is possible to embed the EKF algorithm to the ARM processor of PI-WINS - it will result in a more accurate solution but will also lead to a shorter battery operation time and inevitable solution time lag.

When the car enters a parking garage ("parking garage entry" mark on Fig.10) the reference GNSS/INS solution actually drifts more than the PI-WINS solution. The maximum 2D position error of PI-WINS is below 10 meters. This test shows the potential of the system, and we are running an extensive test campaign with other types of additional sensors such as Lidars, stereo cameras and precise point positioning receivers. This campaign will help to reveal the pros and cons of wheel-mounted systems with different kinds of sensor setups.

There are many other applications and test scenarios one may run with wheel PI-WINS sensors, analysis and discussions of which will surely not fit into one paper. For example, having several PI-WINS sensors on front and rear wheels can be very useful in detecting wheel slips. Data from 4 PI-WINS installed on all vehicle wheels can be used to estimate the radius and center of curvature of the path the car drives at. PI-WINS' raw 2kHz inertial data is a perfect information to analyze wheel dynamics and road conditions. In this paper, we just scratched the surface and showed rather navigation-related results - more relevant to the field of expertise of the authors.

VI. Conclusions

Availability, reliability and integrity of vehicular navigation technology become more and more critical as autonomous transport systems enter the market with high volume. To enable continuous operation, cameras and LiDARs equipped with modern machine learning algorithms are being coupled with traditional GNSS and inertial navigation systems. When considering system tolerance to interference (intentional or unintentional) inertial sensor based solutions are in their own class. Thus, improving performance of inertial systems while keeping the costs at reasonable level is worth studying. In this article we have shown that inertial measurement unit mounted to the wheel of a vehicle can be used as a hi-rate (2 kHz) source of bias-free data for a) vehicle navigation b) instantanious wheel dynamics estimation (angles, rates, accelerations) for vehicle stability control c) road quality measurement systems. As the MEMS biases have no effect in the result the resolution capabilities at low dynamic conditions are exceptional. The described method opens potentially new methods for car stability systems and autonomous driving. We invite research groups and industry to join us in exploration of what this technology can bring to vehicular navigation, monitoring and stability systems in the near future.

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