

# Motion State Acquisition and Error Analysis for Intelligent Vehicle Power Management Strategies

DongPing Song, WuLing Huang, YuQiang Liu, Tao Sun, DaLei Guo  
Institute of Automation, Chinese Academic of Sciences, Beijing, China  
songdongping2004@126.com

**Abstract**—Intelligent Vehicles acquire driving environment information and it self's attitude using several kinds of sensors. Then through data fusion, it implements driving assistant system and even automatic/autonomous driving. This article focuses on vehicle motion state acquisition and error analysis for driving patterns recognition, which is needed by intelligent power management strategies. With low cost MEMS sensors and low accuracy data processing model, vehicles' velocity, acceleration and gyroscope data can be acquired and analyzed, which can be used in driving patterns recognition. Because of the high interference of dynamic driving environment and low accuracy of MEMS sensors, common errors appear in sensor data acquisition and methods to eliminate the deviations are also discussed, with experiments and data analysis presented.

**Keywords**—Power Management Strategies; Motion State Acquisition; MEMS Sensors; Data Filter; Errors Analysis

## I. INTRODUCTION

Intelligent Vehicles acquire driving environment information and it self's attitude using various kinds of sensors [1-2]. Driving assistant and automatic driving system require several kinds of sensor data and then percept the environment through data fusion [4-7]. This article focuses on vehicle motion state acquisition and error analysis for driving patterns recognition system, which is needed by intelligent power management strategies. It is important to get more accurate driving cycles, vehicle operating mode and driving styles for implementation of an intelligent power management system because several studies show that they are critical factors of power consumption [10-14]. It seems that it is more feasible to implement this kind of system with low cost MEMS sensors; however, the low accuracy is the additional cost. This article discusses data acquisition and processing model based on MEMS sensors installed on vehicles, focuses on the errors analysis with several kinds of error analysis. It aims to provide more accuracy and stable data for power management system.

This article are organized as following: The first section bring out the proposed vehicle information collecting system used for driving pattern recognition, the second part is error discussion of vehicle attitude collection, and the last section of this article gives speed, acceleration and gyroscope deviation analysis, and several error analysis methods are discussed and results are presented.

## II. VEHICLE MOTION STATE ACQUISITION FOR DRIVING PATTERN RECOGNITION

Intelligent Vehicle acquires driving environment information including road types and traffic congestion level

collection and emergency events detection. And it also needs to know it self's motion state to implement more intelligent manipulation [6]. The data is input into driver or automatic driving program to control the vehicle after data fusion. Through vehicle operation mode and driving styles perception, the power needs are fed back to power management system.

To recognize the driving patterns, it is necessary to collect vehicles' speed, turning angle, acceleration, clutches and brake pedal statuses etc. Our proposal system uses MEMS sensors to collect parts of the information and use algorithms to recognize and predict the driving patterns. The proposed system we designed contains MCU, MEMS acceleration module, gyroscope module and speed acquisition module. The hardware diagram is described as Fig.1.

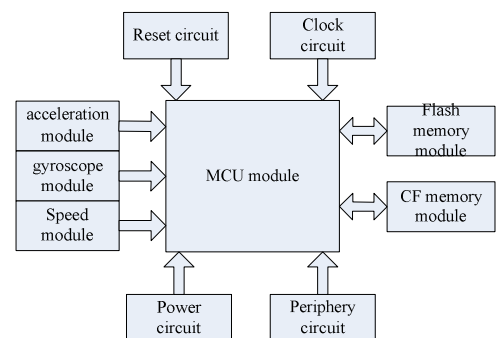


Fig 1. Vehicles Motion State Acquisition Prototype System

MCU is Philips LPC 2378 with ARM7 core, integrated FLASH/SRAM Memory, ADC/USART and CAN 2.0B modules. MEMS acceleration module is a low cost capacitive accelerometer MMA7260QT which has signal conditioning and temperature compensation. Gyroscope module is ADI ADXRS613, which can accurate measure shifting angle and rotating angular speed. Speed sensor is a DIY sensor to get wheel speed.  $\mu$ C/OS-II is used for real time speed, acceleration and gyroscope data acquisition and procession tasks.

Driving environment is high dynamic and with lots of interference, especially when vehicle is on start-up, reversing, braking and going to a stop. Additionally, the structure distortion of vehicle will also affect some sensors data collection. Only after time and space coordination calibration and then digital filtering, several kinds of noises and errors can be eliminated. If it is possible, redundancy sensors should be used to get more accurate and reliable data. This

paper focuses on collection and preprocessing of sensor data about data fusion. It is described as Fig.2.

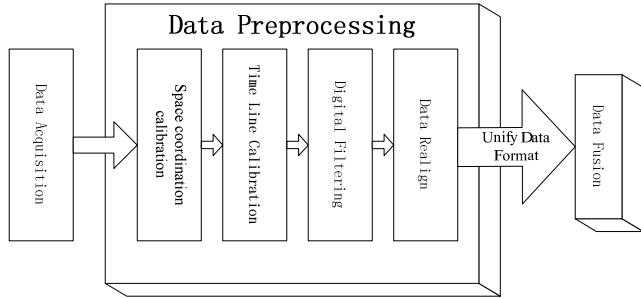


Fig 2. Sensor Data Calibration Procession

### III. VEHICLE MOTION STATE ACQUISITION ERRORS ANALYSIS

#### A. System Errors Discussion

There are usually initial deviation, temperature drift and random error existing in sensors acquisition data. The initial deviation is a kind of sensor system error, which is related to environment operation temperature and features of the sensors, such as MEMS sensor manufacturing error, PCB flatness and initial position deviation during welding. The temperature drift is mainly the result of temperature variation which contributes to the drift of working point, such as the influence of the T2 cycle of the MEMS sensor, which needs to be undertaken temperature compensation. The random error of the MEMS sensor is the most important influences factors which are related to the performance of the devices. Besides, there is usually rough error to be got rid of as a result of measuring instruments, measuring method and conditions are not normal or the error operating of survey crews. And since power supply noise and electromagnetic interference exist in the system, the analog input signal will be superposed with periodic or non-periodic interference signals which will be added to quantitative values. What's more, some other factors, such as the A/D converter resolution, the filter's designed bandwidth and the effect on device resolution on account of the counting frequency of the timer, will result in the error of data acquisition.

Since several kinds of MEMS sensors are used in our prototype system, the errors are inevitably. The resolution of the velocity sensor has certain resolution limit and the tires charged level are different, there will be certain accumulative error. Both MEMS accelerometers and gyroscopes are also with initial deviation, temperature drift and random error [9].

#### B. Error Elimination Methods

Classic loop feedback control method can be used to decrease system error. Kalman filtering method can also be used to estimate the system error and eliminate them with the optimal probability and statistics. Because of the MEMS sensor random error, it is considered to be with better performance than the former method [3].

To solve the problem of the MEMS sensor's A/D sampling error, data acquisition filtering should be added to reduce the interference. Low pass filter can be implemented with hardware of the MEMS sensor system to filter the high

frequency interference. Besides, in the software design, digital filter can be programmed both in the time domain and frequency domain to eliminate the errors, such as the common used limiting filter, median value filter, arithmetic average filter and IIR/FIR filter in frequency-domain [9]. According to the fact that the sampling value fluctuates around a numerical, the arithmetic average filter, median value filter and limiting filter are always used preferentially.

To solve the existence problem of MEMS accelerometers and gyroscopes' initial position deviation, it is necessary to keep the system still for a period of time when the sensors start working. According to the sampling data and modified formula, the initial deviation can be estimated to correct the initial error. In addition, because of the change of the MEMS sensor's working temperature caused the drift of working point, the temperature compensation can be done to calibrate error. Also it is necessary to enhance sampling frequency and reduce bandwidth to reduce the noise and improve resolution.

In this prototype system, limiting average filtering method such as A/D filtering algorithm through experiment are selected. That is to say, we used limiting processing on sampling data and then we enter data into queue for recursive average filtering processing. By combining the advantages of both limiting algorithm and recursive average filtering algorithm, we overcame pulse disturbance caused by occasional factors effectively and have a good inhibition effect on periodic interference with high smoothness at the same time. After establishing suitable MEMS devices model, we needed to select proper filtering algorithm. In engineering practice, Kalman filter is the most widely used and efficient filter algorithm. Through the recursive linear minimum variance estimation process, we could make optimal estimation to improve the data acquisition accuracy after getting the model of random errors [8].

### IV. VEHICLE MOTION STATE ACQUISITION ERRORS ELIMINATION METHODS

#### A. Vehicle Speed Acquisition Errors Elimination

The vehicle speed is measured by the speed sensor which is installed outside the vehicle near the wheels. It is shown in Fig.3. When installing the device, keeping the shaft of device and the axle in the same level is required. This speed acquisition device will generate pluses which are created by sensors (photoelectric sensor or hall sensor). The pulse will be transmitted to MCU via the signal line. When MCU capture the signal and record the time, the acquisition system can calculate the real-time speed while it knows the wheel diameter.

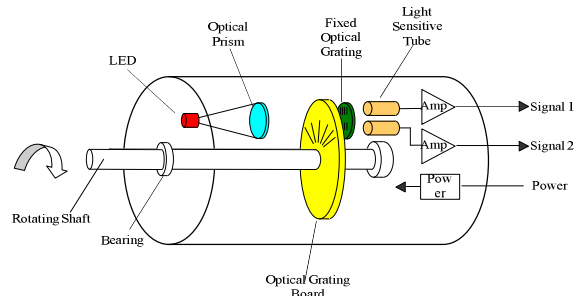


Fig 3. Vehicle Speed Acquisition Sensor

According to the speed acquisition approach and device above, the system has two methods to compute speed: one method is that the distance is fixed, measuring the time interval of two adjacent pulses, as Fig.4 shows; another is measuring the distance during a fixed time interval. The two methods both need deviation analysis.



Fig 4. Scheme of Speed deviation analysis

We analyze the deviation of the first method as an example. As shown in Fig.4, the  $\Delta t$  is the sampling period. The time axis has the moment  $t_x, t_y, t_x + \Delta t, t_y + \Delta t, t_a$  and  $t_b$ . The  $t_a$  is the moment that the MCU receives a pulse from speed sensor. The  $t_b$  is the moment that the MCU receives a second pulse. The  $\Delta x$  is the time interval between  $t_a$  and  $t_x$ . The  $\Delta y$  means the time interval between  $t_b$  and  $t_y + \Delta t$ . On the assumption that the distance between the gratings on the board is  $S$ . The  $T_T$  means the true value of time interval between  $t_a$  and  $t_b$ :  $T_T = t_b - t_a = (t_y + \Delta t) - t_x - \Delta x - \Delta y$ . The  $T_m$  is the time interval calculated by the MCU between  $t_a$  and  $t_b$ :  $T_m = t_y - t_x$ . So  $V_T = S / T_T$ , and  $V_m = S / T_m$ . The  $\Delta V = (V_T - V_m) / V_T = \Delta t / (T_T + \Delta t)$ . The conclusion is that: the error incurred by this method will become smaller as the vehicle speed decreases or the system sampling period gets shorter.

It is the same as the example, we can conclude from the second method that the error incurred by this method will become smaller as the vehicle speed increases or the distance of two adjacent gratings gets shorter. Compared with the two methods, we can conclude that three factors affect the deviation of vehicle speed calculation: First, the sampling frequency; Second, the speed of the vehicle; Third, the distance of two adjacent gratings.

#### B. Kalman filter Used in MEMS Sensors

The Kalman filter is widely used in engineering and is the most effective algorithm. Actually, the Kalman filter which does optimal estimation to improve the precision of the data is a process of linear minimum variance recursive state estimation. In order to meet the stationary sequence, first we should pre-process the random error from the MEMS device, then using the timing sequence model to model the device. We choose AR(1) algorithm [4] to model the random noise. The model of AR (1) is:

$$x_n = -a_1 x_{n-1} + \varepsilon_n. \quad (1)$$

The model shows that the value of  $x_n$  at moment  $n$  is related with the  $x_{n-1}$  at moment  $n-1$ . The  $\varepsilon_n$  is white noise.

After using AR (1) model to describe the stochastic error, the Kalman equation can be defined as follows:

$$x_n = Ax_{n-1} + \varepsilon_n. \quad (2)$$

$$z_n = Hx_n + v_n. \quad (3)$$

Where  $\varepsilon_n$  is white noise, the  $v_n$  is observation noise. On the assumption that the covariance of  $\varepsilon_n$  and  $v_n$  is  $Q$  and  $R$  respectively. Then Kalman filter can be defined as follows:

$$K_n = P_{n,n-1} H^T (H P_{n,n-1} H^T + R)^{-1} \quad (4)$$

$$x_{n,n} = x_{n,n-1} + K_n (z_n - Hx_{n,n-1}). \quad (5)$$

$$P_{n,n} = (I - K_n H) P_{n,n-1}. \quad (6)$$

$$x_{n,n-1} = Ax_{n-1,n-1}. \quad (7)$$

$$P_{n,n-1} = AP_{n-1,n-1} A^T + Q. \quad (8)$$

### V. GYROSCOPE AND ACCELERATION DATA DEVIATION ANALYSIS

#### A. gyroscope data and analysis

Angular rate is gathered from ADXRS613 which is running in a static environment at laboratory. The sampling frequency is 50 HZ. The A/D filter is described above, the upper bound is set 250 mv, and the lower bound is -250 mv. As we can see, the variance of data reduces a lot after convergence. In Fig. 5a, the variance of the original data is 0.2676; after KF convergence, the variance is reduced to 0.0379, the data are shown in Fig. 5b.

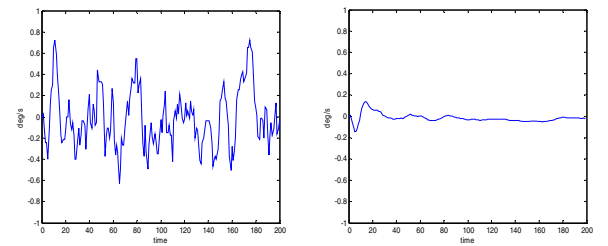


Fig 5. gyroscope data and analysis

#### B. Acceleration data and analysis

MEMS accelerometer is different from gyroscope, the accelerometer suffers heavy interference when it was installed on a vehicle. Most of the signal noise is distributed at 25 HZ, they are engine noise [5]. Wavelet de-noising which is described in reference is an effect method to eliminate noise. In order to get idea acceleration information,

the Kalman filter can be used to do data compensation after the wavelet de-noising algorithm.

Acceleration data is from MMA7260QT. The sampling frequency is 50 HZ. Because the accelerometer is tested at laboratory environment, wavelet de-noising is not needed. The experimental data is showed from Fig. 6

We can conclude from the figures that the algorithms can obtain a good effect both at static environment and dynamic environment. Compared with Fig. 6a and Fig. 6b, variance in Fig. 6a is 0.04, but it reduces to 0.0046 in Fig. 6b. In Fig. 6a, there is a heavy interference near time 60, and the acceleration is near -0.2g. But we can't see any interference in Fig. 6b near time 60, the algorithms have eliminated the interference.

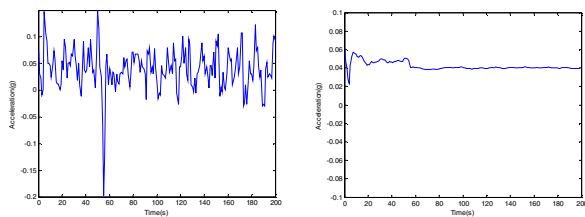


Fig 6. Acceleration data and analysis

## VI. CONCLUSION

This article discusses the common errors of MEMS sensors used in vehicles, also discusses MEMS sensors data acquisition and processing model, especially focuses on the errors analysis with several kinds of error analysis. It aims to provide more accuracy and stable data with low cost and low accuracy MEMS sensors. The acquisition data is used for driving pattern recognition, which is part of intelligent vehicle power management system. A prototype vehicle information collecting system is presented and error analysis of speed, acceleration and gyroscope deviation, and several error analysis methods are also discussed and results are presented. The next step is to implement more accurate system and more effective algorithms which can run on embedded system.

This work was supported in part by National Natural Science Foundation of China projects 60921061, 70890084, 90920305, 90924302, 60904057 and 60974065.

## REFERENCES

- [1] Di Lecce, V.; Amato, A.; , "A distributed measurement system for smart monitoring of vehicle activities," Instrumentation and Measurement Technology Conference (I2MTC), 2010 IEEE , vol., no., pp.903-907, 3-6 May 2010
- [2] Maeder, U.; Morari, M.; , "Attitude Estimation for Vehicles with Partial Inertial Measurement," Vehicular Technology, IEEE Transactions on , vol.PP, no.99, pp.1, 0
- [3] Khitwongwattana, A.; Maneewarn, T.; , "Extended Kalman Filter with Adaptive Measurement Noise Characteristics for Position Estimation of an Autonomous Vehicle," Mechatronic and Embedded Systems and Applications, 2008. MESA 2008. IEEE/ASME International Conference on , vol., no., pp.505-509, 12-15 Oct. 2008
- [4] Bevilacqua, D.M.; Ryu, J.; Gerdes, J.C.; , "Integrating INS Sensors With GPS Measurements for Continuous Estimation of Vehicle Sideslip, Roll, and Tire Cornering Stiffness," Intelligent Transportation Systems, IEEE Transactions on , vol.7, no.4, pp.483-493, Dec. 2006

- [5] Mangan, S.; Wang, J.; Wu, Q.H.; , "Measurement of the road gradient using an inclinometer mounted on a moving vehicle," Computer Aided Control System Design, 2002. Proceedings. 2002 IEEE International Symposium on , vol., no., pp. 80- 85, 2002
- [6] Tang-Hsien Chang; Chih-Sheng Hsu; Chieh Wang; Li-Kai Yang; , "Onboard Measurement and Warning Module for Irregular Vehicle Behavior," Intelligent Transportation Systems, IEEE Transactions on , vol.9, no.3, pp.501-513, Sept. 2008
- [7] Liu Jun; Wang Sumei; Pan Ke; Xie Jun; Wang Yun; Zhang Tao; , "Research on On-line Measurement and Prediction for Vehicle Motion State," Digital Manufacturing and Automation (ICDMA), 2010 International Conference on , vol.2, no., pp.247-250, 18-20 Dec. 2010
- [8] Gao Zhenhai; , "Soft sensor application in vehicle yaw rate measurement based on Kalman filter and vehicle dynamics," Intelligent Transportation Systems, 2003. Proceedings. 2003 IEEE , vol.2, no., pp. 1352- 1354 vol.2, 12-15 Oct. 2003
- [9] Dissanayake, G.; Sukkariyah, S.; Nebot, E.; Durrant-Whyte, H.; , "The aiding of a low-cost strapdown inertial measurement unit using vehicle model constraints for land vehicle applications," Robotics and Automation, IEEE Transactions on , vol.17, no.5, pp.731-747, Oct 2001
- [10] Langari, R.; Won, J.-S.; : Intelligent energy management agent for a parallel hybrid vehicle-part I: system architecture and design of the driving situation identification process. IEEE Transactions on Vehicular Technology 54(3), 925-934 (2005)
- [11] Syed, F.U.; Filev, D.; Ying, H.: Fuzzy Rule-Based Driver Advisory System for Fuel Economy Improvement in a Hybrid Electric Vehicle. In: Annual Meeting of the NAFIPS, June 24-27, pp. 178-183 (2007)
- [12] Sciarretta, A.; Guzzella, L.; Back, M.: A real-time optimal control strategy for parallel hybrid vehicles with on-board estimation of the control parameters. In: Proc. IFAC Symp. Adv. Automotive Contr., Salerno, Italy, April 19-23 (2004)
- [13] Zhihang Chen; Abul Masrur, M.; Murphey, Y.L.; , "Intelligent vehicle power management using machine learning and fuzzy logic," Fuzzy Systems, 2008. FUZZ-IEEE 2008. (IEEE World Congress on Computational Intelligence). IEEE International Conference on , vol., no., pp.2351-2358, 1-6 June 2008
- [14] Zhihang Chen; Kiliaris, L.; Murphey, Y.L.; Masrur, M.A.; , "Intelligent power management in SHEV based on roadway type and traffic congestion levels," Vehicle Power and Propulsion Conference, 2009. VPPC '09. IEEE , vol., no., pp.915-920, 7-10 Sept. 2009
- [15] Sebastian Thrun, Probabilistic robotics, Communications of the ACM, v.45 n.3, March 2002.
- [16] Wu-Ling Huang, Xin Qiao, Yunfeng Ai, Qingming Yao, "An Integrated Automotive Software Development and Validation System Based on CASOS-OSEK", Proceedings of the 4th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications, Beijing, China, 2008: 269-274.
- [17] Yuan Sun, Wu-Ling Huang, Shu-Ming Tang, Xin Qiao, and Fei-Yue Wang, "Design of an OSEK/VDX and OSGi-based Embedded Software Platform for Vehicular Applications", IEEE International Conference on Vehicular Electronics and Safety(ICVES), December, 2007.
- [18] Wang Fei-Yue, Tang Shuming, "Concepts and Frameworks of Artificial Transportation Systems", Complex Systems and Complexity Science, vol.1, no.2, pp.52-59, 2004.
- [19] Wang Fei-Yue, Tang Shuming, "Artificial Societies for Integrated and Sustainable Development of Metropolitan Systems", IEEE Intelligent Systems, vol.19, no.4, pp. 82-87, 2004.
- [20] Wang Fei-Yue, "Parallel Control and Management for Intelligent Transportation Systems: Concepts, Architectures, and Applications", IEEE Transactions on Intelligent Transportation Systems, vol.11, no.3, pp.630-638, 2010.
- [21] Zhu Fenghua, Li Guoxi, Li Zhenjiang, Chen Cheng, Wen Ding, "A Case Study of Evaluating Traffic Signal Control Systems using Computational Experiments", IEEE transactions on Intelligent Transportation Systems, 2011, accepted.
- [22] Wang Fei-Yue, "Agent-Based Control for Networked Traffic Management Systems", IEEE Intelligent Systems, vol.20, no.5, pp.92-96, 2005.

- [23] Wang Fei-Yue, Wang Cheng-Hong, “On Some Basic Issues in Network-Based Direct Control Systems”, *Acta Automatica Sinica*, vol.28, Supp1, pp. 171-176, 2002.