

## Combined Information Processing from GPS and IMU using Kalman Filtering Algorithm

V. Bistrovs, A. Kluga

Department of Transport electronics and telematics, Riga Technical University,  
Lomonosova iela 1, V korpuss, LV-1099, Riga, Latvia, e-mail: bistrov@inbox.lv, ansis.kluga@rtu.lv

### Introduction

GPS and micro-electro-mechanical (MEMS) inertial systems have complementary qualities that make integrated navigation systems more robust. The development of GPS is used to provide the navigation data, but the performance is limited in areas where poor satellite visibility environment exists. When it comes to land vehicle application and telematics, integration is particularly required in urban canyon areas where the signal from the satellites is susceptible to blocking or detracting by high story building or trees.

From other side bias offset drift exhibited in the acceleration signal is accumulative and the accuracy of the distance measurement can deteriorate with time due to the integration. This problem can be fixed by periodic recalibration with the help of external measurements (GPS) of position. Hence, sensor fusion including IMU (Inertial Measurement Unit), GPS (Global Positioning System) is required to provide the vehicle's position to telematics service provider and driver behind the wheel.

Current research and study have emphasized on using low cost IMU and GPS integration by the benefit of computing power and low price of IMU. The vehicle kinematics is obtained by a Holux GPS and a Motion Node IMU sensor.

### Data Acquisition System

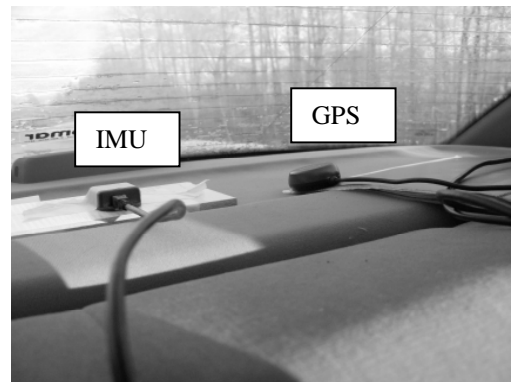
In terms of equipment, the experiment setup used a low cost MEMS (Micro-Electro-Mechanical-System) IMU (Inertial Measurement Unit) Motion Node, low cost GPS receiver Holux GR-213U, and a notebook to process and save the data. This equipment was placed inside vehicle (Fig.1).

The commercial IMU-MEMS (Motion Node) used in the experiment is composed of three accelerometers, three gyros, three magnetometer with USB interface output (2009, GLI Interactive LLC). This strapdown inertial system provides measurement of linear acceleration, angular velocity, magnetic field strength (only

accelerometers' signals are used in current research). The accelerometer characteristics are presented in Table 1.

**Table 1.** Specifications of Motion Node accelerometer

Measures	Linear acceleration
Range/Sensitivity	$\pm 2g$ or $\pm 6g$
Resolution	$0.001g \pm 10\%$ (at 2g range)
Noise density	$0.00005g/\sqrt{Hz}$ (at 2g range)



**Fig. 1.** Equipment installation

The data acquisition was performed through a USB communication port, whose protocol is a GLI Interactive LLC proprietary format. Its maximum sampling rate is 100Hz configurable (60Hz used during experiments).

The HOLUX GR-213 Smart GPS Receiver is a total solution GPS receiver, designed based on SiRF Star III Architecture. It communicates with other electronic utilities via USB interface. With low power consumption, the GR-213 tracks up to 20 satellites at a time, re-acquires satellite signals in 100 ms and updates position data every second. GPS receiver and IMU device were connected via USB interfaces to notebook. VisualGPS software was used for NMEA data acquisition and saving to txt file

format on notebook hard disk drive. Motion Node software was used for the same purpose but for the IMU data.

The experiment is conducted such that initially the IMU is warmed up to avoid thermal transients during the experiments. Motion Node is rigidly mounted inside car (Fig.1) so that direction of its X-axis would be along road direction

The IMU coordinate system is shown in Fig. 2.

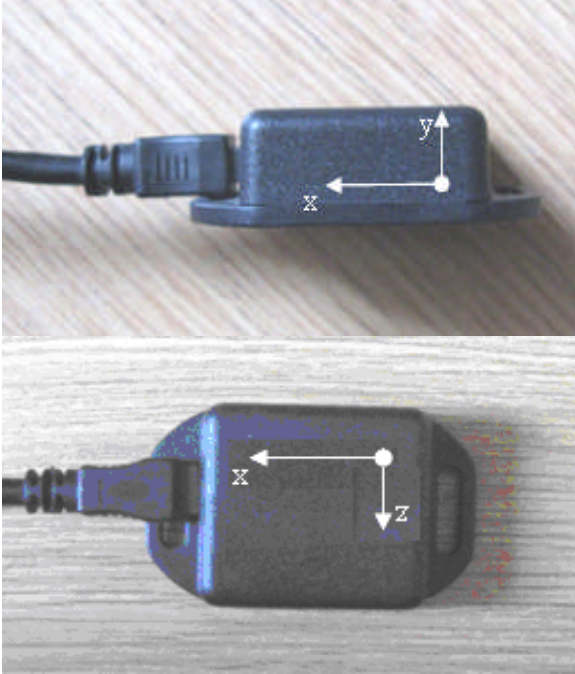


Fig. 2. IMU coordinate system

IMU Motion Node was fixed rigidly on a board inside vehicle in order the sensor reference frame (Fig. 2) coincided with vehicle reference frame (Fig. 3). The experiments were conducted on the straight good quality road (Fig. 4).



Fig. 3. Vehicle reference frame

### Combined data processing from GPS and IMU sensors

In the approach, GPS and INS data is processed by linear Kalman filter. The GPS data are taken as external measurement input, while the INS data are taken as additional information to the Kalman filter's state

prediction. The external measurements for data processing algorithm are MEMS accelerometers' signals along x and y axis and estimated distance along x-axis using GPS receiver measurements. The output parameters of data processing algorithm are estimations of vehicle's acceleration, velocity, distance and accelerometer bias.

The advantage of this approach is that a simple and linear Kalman filter can be implemented to achieve significant computation saving.

The commonly used stochastic error model for accelerometer is [1]:

$$f_{acc} = (1 + S) \cdot a + b + \eta, \quad (1)$$

where  $f_{acc}$ - accelerometer's measurements,  $S$ - scale factor of accelerometer,  $b$ -bias of accelerometer,  $\eta$ -random bias or random component of measurements,  $a$ -acceleration value.

The scale factor and bias of the accelerometer is calibrated by the manufacturer. But post-factory calibration of the instrument can still influence the navigation performance significantly, therefore it can also be considered in the stochastic error model. Post-factory calibration results in research paper [2] show that there's real need for extra error (accelerometer bias and random component) compensating of accelerometer signal, but the impact of accelerometer scale factor can be negligible for the conducted experiments in this paper.

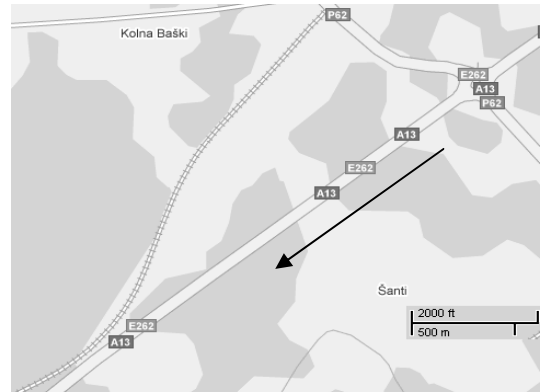


Fig. 4. Route taken for experiments

Basically, the Kalman filtering estimation algorithm comprises two steps, namely prediction and update with external measurements. The formulation of linear Kalman filter can be found in [3]. The corresponding elements of linear Kalman processing algorithm are shown below:

$$\Phi_k = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ T & 0 & 1 & 0 & 0 & 0 \\ 0.5 \cdot T^2 & 0 & T & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}, \quad (2)$$

where  $\Phi_k$  – state transition matrix,  $T$  – time interval between sensor measurements.

$$\mathbf{H}_k = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 \end{bmatrix}, \quad (3)$$

where  $\mathbf{H}_k$  – measurement transition matrix.

$$\mathbf{Z}_k = [f_x \quad s_{x\_GPS} \quad f_y], \quad (4)$$

where  $\mathbf{Z}_k$  – measurement vector,  $f_x$  – accelerometer measurements along  $x$  axis,  $f_y$  – accelerometer measurements along  $y$  axis,  $s_{x\_GPS}$  – calculated distance passed by vehicle using GPS measurements.

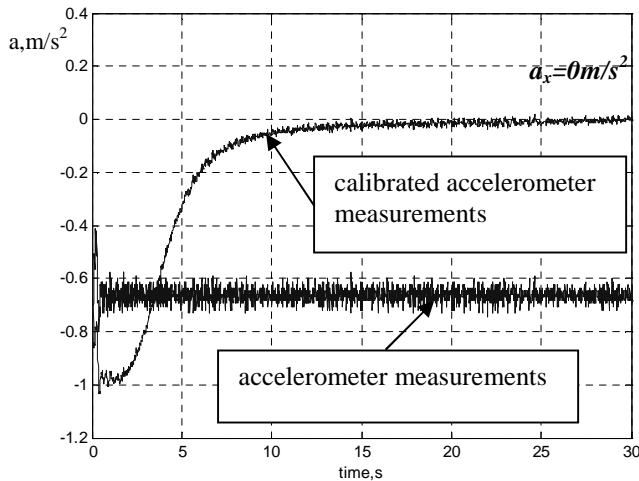
$$\mathbf{X}_k = [a_x \quad b_x \quad v_x \quad s_x \quad a_y \quad b_y], \quad (5)$$

where  $\mathbf{X}_k$  – system state vector;  $a_x$  – estimated vehicle acceleration along  $x$  axis;  $a_y$  – estimated vehicle acceleration along  $y$  axis;  $b_x$  and  $b_y$  – estimated biases of accelerometers;  $v_x$  – estimated vehicle velocity;  $s_x$  – estimated distance passed by vehicle.

### Kinematics test results

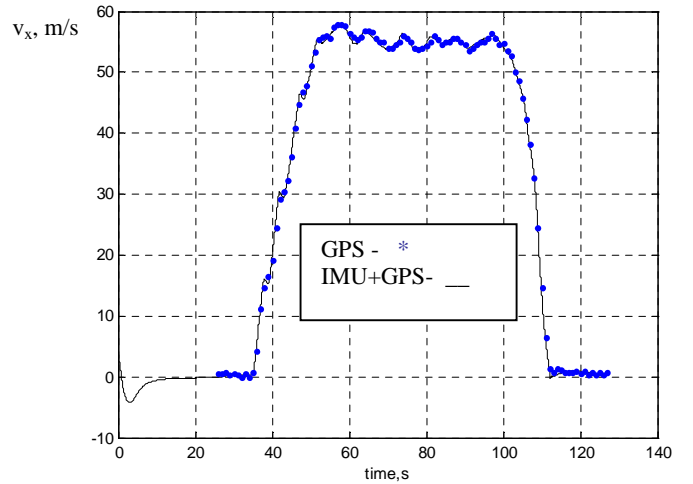
There're conducted kinematics tests for different dynamic characteristic of moving vehicle. There're three stages of the vehicle moving during experiments acceleration till the defined value of velocity, almost uniform movement with defined velocity and braking. The vehicle velocities according speedometer indication during uniform movement were approximately  $v = 40, 60, 80$  km/h. The distance passed by vehicle always was around  $1004 \pm 1$ m. This distance interval was specially identified and measured on the road.

Before to present results of experiments, we will show that postcalibrating of accelerometer's measurements data is really necessary. Accelerometer measurements before and after postcalibration process using Kalman linear filter defined in previous section are shown in the Fig. 5. The real acceleration value of the vehicle was  $0 \text{ m/s}^2$  during postcalibrating process. From Fig. 5 we can see that acceleration value after 15 s of postcalibrating process is very near to zero. Also it can be noticed that the level of measurement noise decreases.

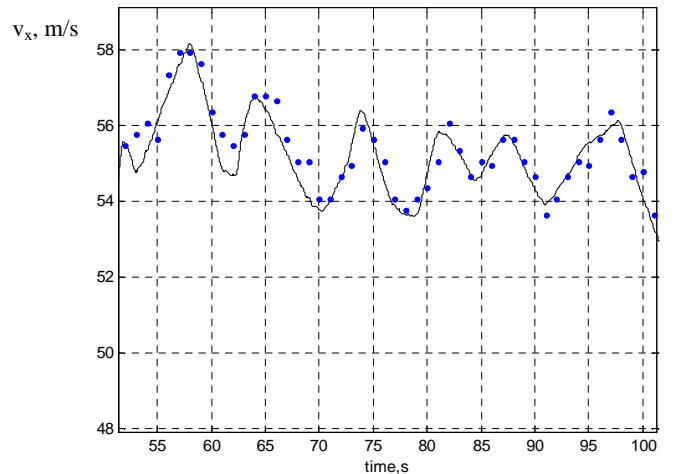


**Fig. 5.** Accelerometer measurements before and after postcalibration process

Now we present results of combined data processing from IMU and GPS sensors. The vehicle velocity and accelerometer bias estimation results using GPS and accelerometer data are shown in Fig.6-13. There're discrete points near each curves of velocity estimation (Fig.7,10,12) that correspond to velocity estimated values using only GPS measurements and curve correspond to velocity estimation using data fusion from GPS and IMU sensors. There're fluctuations of estimated velocity value during almost uniform stage of vehicle moving (Fig.7). This is due to the vehicle driving process itself, as it's impossible to keep very precise velocity of vehicle during experiments. There're some clearly seen peaks on the curve of estimated velocity during vehicle acceleration (Fig.8). These peaks are due to the vehicle gear shifting.

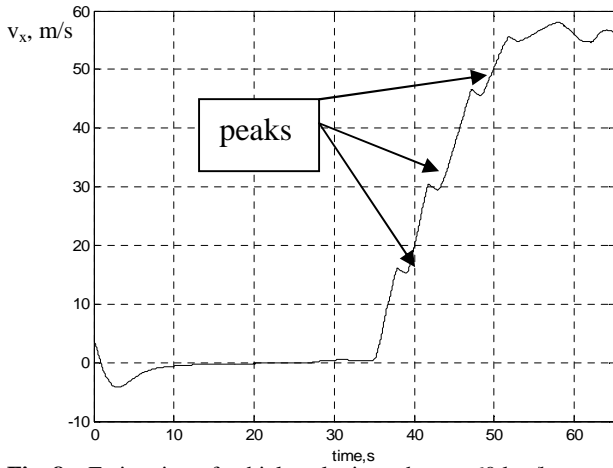


**Fig. 6.** Estimation of vehicle velocity, when  $v=60$  km/h

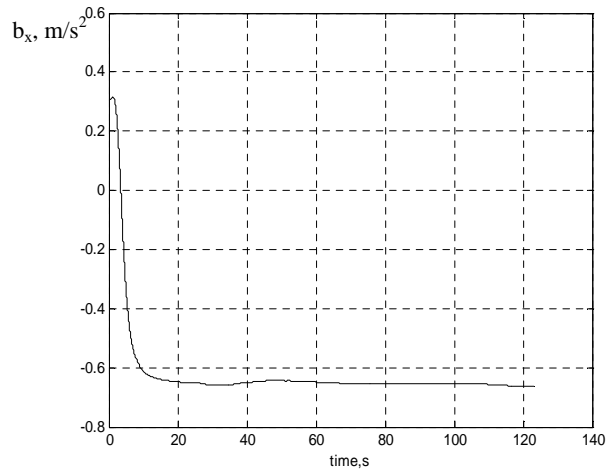


**Fig. 7.** Estimation of vehicle velocity, when  $v=60$  km/h (zooming in of the Fig.6 at time interval from  $t= 50$ s till  $t=100$  s)

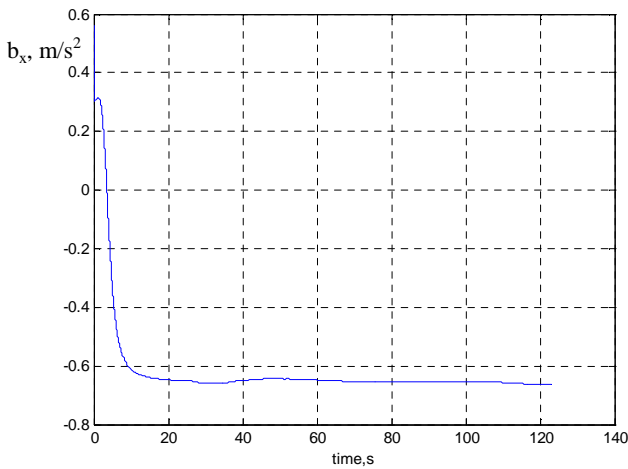
As we can see from Fig. 6, 7, 10, 12, the estimations of velocity using both methods (direct velocity estimation using only GPS measurements and velocity estimation using data fusion from GPS and accelerometer sensors) are almost identical. It's necessary to notice that direct velocity estimation occurs only one time per second (1 Hz), but velocity estimation using data fusion method occurs 60 times (60 Hz) per second.



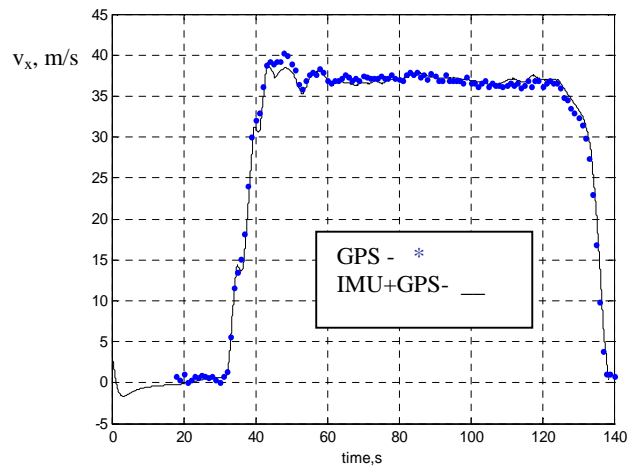
**Fig. 8.** Estimation of vehicle velocity, when  $v=60$  km/h



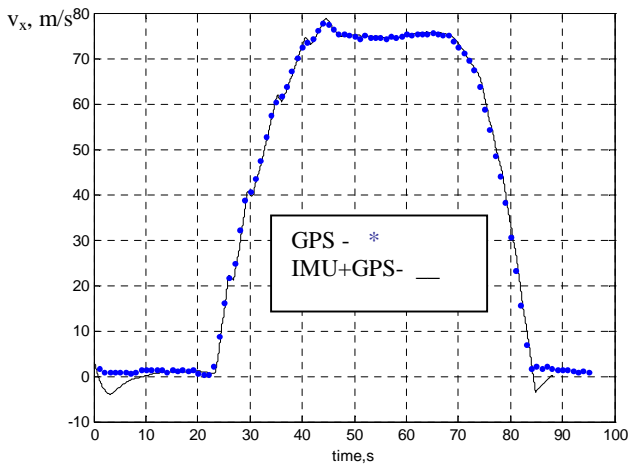
**Fig. 11.** Estimation of accelerometer bias, when  $v=80$  km/h



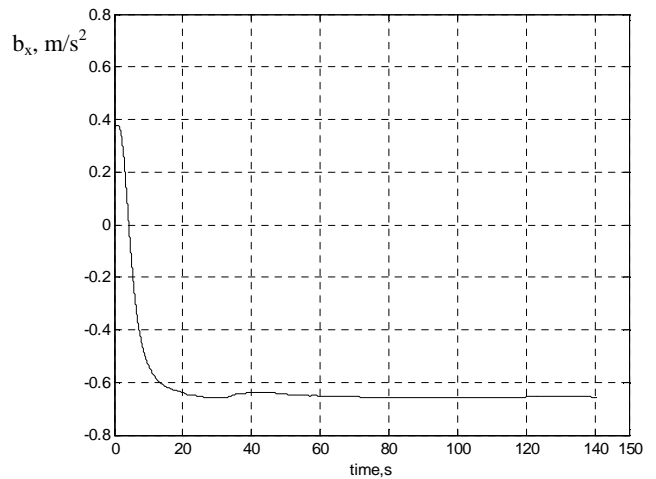
**Fig. 9.** Estimation of accelerometer bias, when  $v=60$  km/h



**Fig. 12.** Estimation of vehicle velocity, when  $v=40$  km/h



**Fig. 10.** Estimation of vehicle velocity, when  $v=80$  km/h



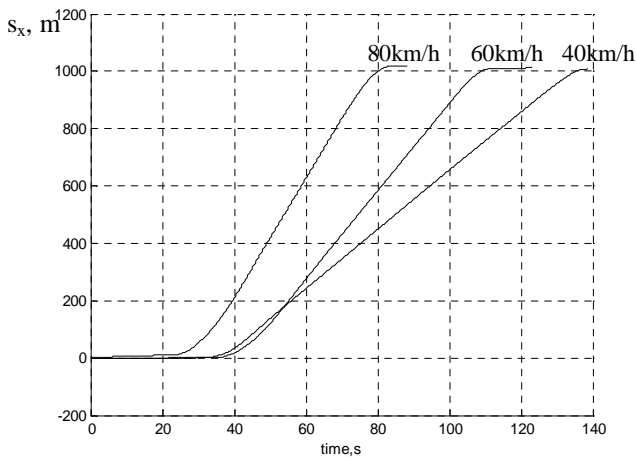
**Fig. 13.** Estimation of accelerometer bias, when  $v=40$  km/h

The results of distance estimation passed by vehicle with velocities 40, 60, 80 km/h are represented in Table 2. The precision of estimated distance is very good for both methods as we can see from the Table 2. The mean error is 5.33 m for the direct method of distance estimation based only on GPS measurements. The mean error is 4.67 m for the combined GPS and accelerometer data processing method using Kalman linear filter. The curves of estimated distances using GPS and IMU data fusion algorithm (Kalman filter) are shown in Fig.14

The kinematics test results presented before was made for the vehicles, which introduce low extra noise. The vehicle noises such as engine noise, vibration have significant impact on the low cost sensor measurements and hence on final navigation solution if the appropriate methods and algorithms are not used for the data processing. Therefore next kinematics test was conducted for the case of increased noise introduced by vehicle.

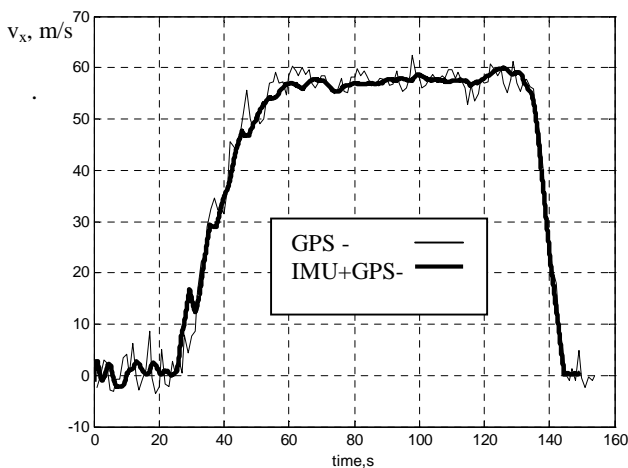
**Table 2.** Estimated distance passed by vehicle

The distance to be passed by vehicle is 1004±1m	Distance estimation method	
	direct using only GPS data	fusion of GPS and accelerometer data
TEST 1 with v=40 km/h	1008m	1007m
TEST 2 with v=60 km/h	1009m	1009m
TEST 3 with v=80 km/h	1011m	1010m



**Fig. 14.** Distance estimation using GPS and IMU data fusion, when v=40, 60, 80 km/h

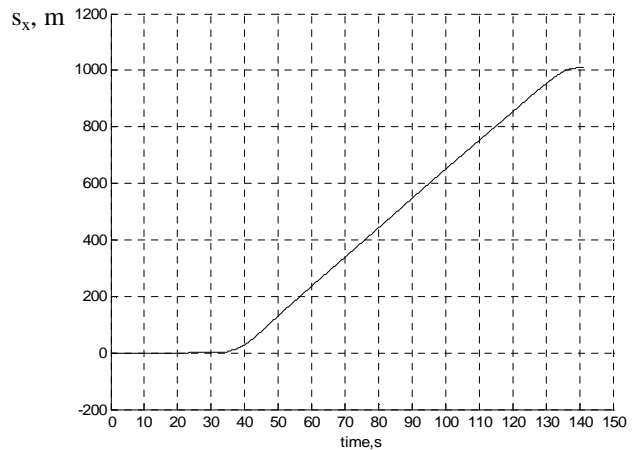
We can notice quite big noisy fluctuation of the velocity estimation based on GPS measurements only (Fig.15). The fluctuations of estimated velocity decrease if we use developed Kalman algorithm for GPS and Motion Node sensor data fusion. The distance estimation error decreases from 16 m to 6 m also if we use combined information processing.



**Fig. 15.** Estimation of vehicle velocity, when v=60 km/h

Further we have investigated impact of GPS signal outage during certain period of time on the distance estimation error. This error was estimated as difference between distance estimations according data processing results when signals from both sensors exist and when

only IMU signal exists. The distance estimation results without any GPS signal outages are represented in Fig.16. The virtual results (we do not use GPS dates for distance calculation) show that distance estimation error increase with time. This error increase is caused by the integration of uncompensated random bias of accelerometer signal, as there're no measurements from GPS receiver to make recalibration of accelerometer signal. These virtual results also show that during 10s-15s of GPS signal outage, there's no significant deteriorating of navigation solution for passed distance. This means that we can have continuous navigation solution, even if short GPS signal outages occur.



**Fig. 16.** Distance estimation using GPS and IMU data fusion, when v=40 km/h

## Conclusions

The developed linear Kalman algorithm for combined data processing from low cost GPS and MEMS IMU (accelerometers) allow obtaining navigation solution (velocity, distance) for moving vehicle, and in case of GPS signal short outages to continue providing navigation solution using only IMU calibrated data. Algorithm allow to reduce noise fluctuation of estimated velocity values and improve precision of distance measurements for the cases of sensor installation inside vehicles with moderate level of vibration and engine noises. The drawback of developed Kalman algorithm is time and resource demanding operation for the filter tuning process.

## References

1. **Titterton David H., Weston John L.** Strapdown. Inertial Navigation Technology. 2nd Edition. – USA, UK: The Institution of Electrical Engineers, 2004. – 581 p.
2. **Bistrovs V.** Analyse of MEMS Based Inertial Sensors Parameters for Land Vehicle Navigation Application // Scientific proceedings of Riga Technical University – Telecommunications and Electronics – Riga. – RTU, 2008. – Vol. 8. – P. 43–47.
3. **Mohinder S. Grewal, Angus P. Andrews.** Kalman Filtering: Theory and Practice Using MATLAB. 2<sup>nd</sup> ed. – John Wiley & Sons, Inc. – 2001.

**V. Bistrovs, A. Kluga. Combined Information Processing from GPS and IMU using Kalman Filtering Algorithm // Electronics and Electrical Engineering. – Kaunas: Technologija, 2009. – No. 5(93). – P. 15–20.**

Inertial Navigation System (INS) and Global Positioning System (GPS) technologies have been widely used in a variety of positioning and navigation applications. Both systems have their unique features and shortcomings. Therefore, the integration of GPS with INS is now critical to overcome each of their drawbacks and to maximize each of their benefits. We present low-cost MEMS inertial and GPS sensor data fusion using a Kalman filter for vehicle distance and velocity estimation. Important parts of the developed Kalman filter that is used to optimally combine data from navigation sensors are described. Then, algorithm performance is illustrated based on an experiment during which the GPS/MEMS-IMU system was installed inside a car. Il. 16, bibl. 3 (in English; summaries in English, Russian and Lithuanian).

**В. Быстров, А. Клуга. Применение фильтра Калмана для совместной обработки GPS и IMU информации // Электроника и электротехника. – Каунас: Технология, 2009. – № 5(93). – P. 15–20.**

Инерциальные навигационные системы (ИНС) и системы глобального позиционирования (СГП) широко используются для решения навигационных задач. Обе системы имеют свои уникальные особенности и недостатки. Поэтому решение задачи интеграции системы глобального позиционирования с инерциальной системой позволяет преодолеть недостатки и максимизировать преимущества каждой из систем. Представлен алгоритм совместной обработки данных от низкостоймостных МЭМС ИНС и СГП сенсоров, используя фильтр Калмана для оценки скорости и пройденного расстояния автомобилем. Представлены основные элементы разработанного фильтра Калмана для оптимальной совместной обработки информации от сенсоров. В ходе тестов МЭМС ИНС и приемник СГП были установлены внутри автомобиля и полученные результаты измерения были использованы для иллюстрации работы разработанного алгоритма. Ил. 16, библи. 3 (на английском языке; рефераты на английском, русском и литовском яз.).

**V. Bistrovs, A. Kluga. Jungtinis GPS ir IMU informacijos apdorojimas panaudojant Kalmano filtravimo algoritimą // Elektronika ir elektrotechnika. – Kaunas: Tehnologija, 2009. – Nr. 5(93). – P. 15–20.**

Inercinių navigacinių sistemų (INS) ir globaliosios pozicionavimo sistemos (GPS) technologijos plačiai naudojamos įvairiose su pozicionavimu ir navigacija susijusiose srityse. Abi sistemos turi unikalių savybių ir trūkumų. Dėl šios priežasties, norint sujungti GPS ir INS sistemas, būtina pašalinti šiuos trūkumus ir maksimaliai išplėtoti jų pranašumus. Pateikiamo tyrimo metu, naudojant Kalmano filtrą, buvo suderinti inercinio MEMS jutiklio ir GPS jutiklio duomenų srautai, pagal kuriuos apskaičiuojamas atstumas iki automobilio ir jo greitis. Aprašomos svarbios sukurtojo ir optimaliai navigacinių jutiklių duomenis jungiančio Kalmano filtro dalys. Algoritmo efektyvumas tirtas eksperimentiškai, naudojant automobilyje įdiegtą GPS/MEMS-IMU sistemą. Il. 16, bibl. 3 (anglų kalba; santraukos anglų, rusų ir lietuvių k.).