

## Distance Estimation using Intelligent Fusion of Navigation Data

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### Introduction

The GPS system complements the inertial system by providing a stable position and velocity output. In fact MEMS (micro-electro-mechanical) inertial systems have moderate bias errors, which are continuously increasing with time; therefore additional vehicle position information from an accurate navigation sensor is required. GPS sensor data helps to estimate the INS bias errors using a navigation filter. The most used technique for sensor data fusing is Kalman filter algorithm.

The general limitations of this algorithm are based on the fact that the integration method has limited intelligence to adapt itself to varying conditions and changing error characteristics. Therefore, intelligent techniques can be used to improve performance navigation algorithm which uses the Kalman filter [1, 2].

In this paper intelligent Kalman algorithm (IKA), that uses rule based system to fuse GPS and accelerometer sensors data, is developed. Conventional rule-based systems use human expert knowledge to solve real-world problems that normally would require human intelligence. Expert knowledge is often represented in the form of rules or as data within computer program.

The developed algorithm performance was compared with one for linear Kalman filter. Experimental results for vehicle passed distance estimation show that IKA has considerably smaller distance estimation error comparing with linear Kalman filter.

The MTi-G (integrated GPS and MEMS inertial measurement unit), distance measuring wheel DigiRoller Plus II were used for experiments in the current research.

### Equipment used in the experiments

The following equipment was used during experiment.

a) *MTi-G sensor from Xsens Technologies [3]*. The MTi-G is a GPS aided MEMS based Inertial Measurement Unit (IMU) and static pressure sensor. The MTi-G IMU contains three accelerometer, three gyroscopes, three magnetometers.

The output of position data from the MTi-G is in Elipsoidal Coordinates (latitude, longitude, altitude) in the WGS-84 Ellipsoid. The MTi-G uses height over ellipsoid – altitude above the ellipsoid (WGS-84).

Sensor readings (acceleration, rate of turn, magnetic field) are in the right handed cartesian coordinate system as defined in Fig.1. This coordinate system is body-fixed to the device. It's possible also to have raw data measurements from sensors and processed data.

The MTi-G has an onboard Attitude and Heading Reference System (AHRS) and Navigation processor. This low-power Digital Signal Processor runs a real-time Xsens sensor fusion algorithm. GPS receiver has the following characteristics:

- receiver type 16 channels L1 frequency, C/A code, GPS update rate 4 Hz,
- start-up time cold start 34 s,
- tracking sensitivity -158 dBm,
- GPS active antenna (active, SMA connector).

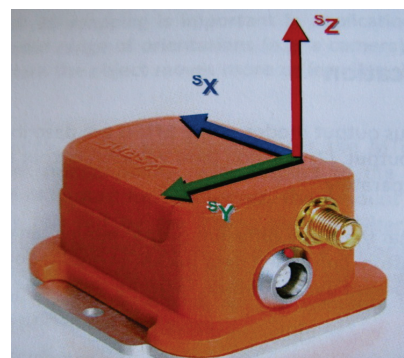


Fig. 1. MTi-G with the default sensor fixed coordinate

b) *Distance Measuring Wheel DigiRoller Plus II* (Fig. 2). Distance Measuring Wheels are excellent tools for measuring long distances. There are different sizes of Distance Measuring Wheels that you can choose from such as; a small wheel for indoor measuring, a medium wheel for both indoor and outdoor, or a large wheel for outdoor only. Generally speaking, the rougher the terrain, the larger the wheel, and the smoother the terrain, the smaller the

wheel. Also, there is a choice of counters and units and there are basically two types of counters to choose from; mechanical or electronic.



**Fig. 2.** Distance measuring wheel system

Distance measuring wheel DigiRoller Plus II uses medium measuring wheel. Medium measuring wheels are great for both indoor and outdoor applications such as measuring large rooms, homes, or warehouses, and outdoor applications like building lots, driveways, sidewalks.

The DigiRoller Plus II Distance measuring wheel will produce quick and accurate measurements with following characteristics:

- measures up to 999,999.9 Feet/Yards/Meters,
  - 99.5% Measuring Accuracy,
  - maximum Speed: 13 km/h.
- c) *Notebook Acer Aspire 5720Z.*

### Experiment description

Measuring wheel is used as reference system for distance value measurement from beginning of motion path to the end. After this value is used as reference value of motion path distance. The motion path of vehicle in experiments was straight without turns. The distance was carefully measured by measuring wheel between fixed guide-posts on the road. (Fig. 3)



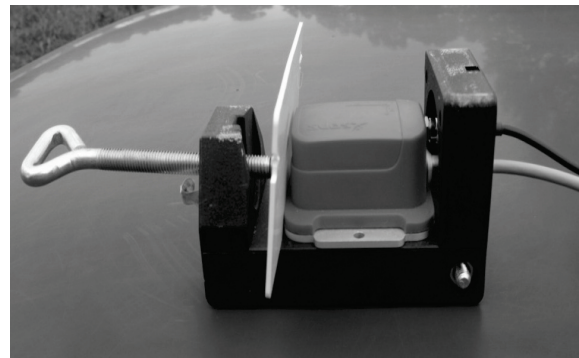
**Fig. 3.** Distance measurement by wheel between guide-posts on the road

The distance measurement between signposts was conducted several times in order to remove (at least decrease) impact of random measurement error on finally obtained reference value of distance. The measured value of distance are shown in the Table 1 below.

**Table 1.** Distance measurements results obtained with measuring wheel.

# Test	1	2	3
Distance,m	1004.47	1005.20	1005.00
# Test	4	5	
Distance,m	1004.85	1005.10	
Mean value,m	1004.9		

MTi-G was fixed rigidly on the support (see Fig.4) that is fixed inside vehicle. The x-axis of MTi-G was directed in the line of vehicle movement. The MTi-G was carefully aligned in space, using special Xsens software feature for calculating orientation of MTi-G in space. This is vitally important for reliable data obtaining from inertial sensor of MTi-G equipment. GPS antenna was placed near MTi-G frame. The distance between GPS antenna and MTi-G frame was 5 cm. During experiments raw data output modes were used for inertial and GPS sensor. This means that Xsens Kalman filter was not used for IMU/GPS data combined processing and physical calibration model also not applied for IMU sensor data [3]. Developed IKA algorithm presented in the paper was used for raw data processing from MTi-G output. Notebook ACER was used for recording data from MTi-G device. MTi-G was connected to notebook via USB port.



**Fig. 4.** MTi-G fixing support

### MTi-G data processing

It's necessary to transform geodetical coordinate (latitude, longitude, height) obtained from MTi-G GPS receiver to ECEF (Earth Centered Earth Fixed) coordinate in order to make combined IMU and GPS data processing.

It's typical to make transformation from latitude, longitude, height to ECEF coordinate system. In order to carry out this transformation, it is necessary to have physical model describing the Earth. The standard physical model used for GPS applications is WGS84. The used algorithm for ellipsoidal coordinates(latitude, longitude, altitude) transformation to X, Y, Z coordinates of ECEF system is presented in [2].

Having sequence of moving vehicle coordinates corresponding to appropriate time epochs, we can determine passed distance.

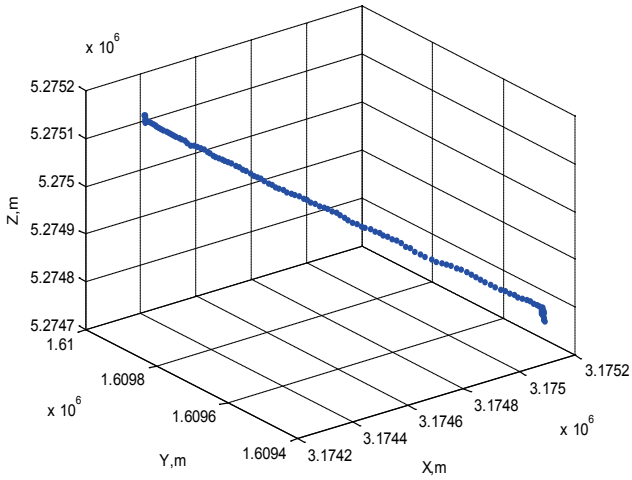


Fig. 5. Vehicle moving path in ECEF system

The interval between time epochs depends on sensor data update rate. In the current experiment the rate of GPS receiver positioning data update was 4 Hz. The rate of data update of the inertial sensor was 50 Hz. Sequence of coordinates (in ECEF frame) for vehicle moving along path is shown in Fig. 5.

In order to find distance passed by vehicle, it's necessary to make successive summing up of all distances between adjacent points on the moving path of vehicle. These points are defined by coordinates in ECEF frame.

### Algorithm outline

Developed algorithm is based on linear Kalman filter. The Kalman filter algorithm and used stochastic model of accelerometer is described in [4, 5]. The measurement vector for intelligent Kalman filter consists of intellectually processed passed distance measurements based on GPS raw data (transformed in ECEF frame), raw accelerometers signals from MTi-G output:

$$\mathbf{Z}_k = [f_x \quad s_{x\_GPS} \quad f_z], \quad (1)$$

where  $f_x$  – accelerometer measurements along x-axis;  $s_{x\_GPS}$  – measured distance passed by vehicle (according raw GPS measurements), which is processed by intelligent algorithm;  $f_z$  – accelerometer measurement along y-axis.

The goal of passed distance measurements processing by intelligent algorithm - is it estimation error decreasing. This error occurs due the noise and uncertainty of measured values by GPS sensor.

The intelligent algorithm working principle is following.

As was mentioned before the passed distance value is determined by successive summing up of distances between adjacent points, which coordinates in ECEF frame defined by GPS measurements:

$$s_{x\_GPS,i} = s_{x\_GPS,i-1} + s_{x\_GPS,i,i-1}, \quad (2)$$

where  $s_{x\_GPS,i}$  – passed distance value at time  $t=t_i$ ;  $s_{x\_GPS,i-1}$  – passed distance value at time  $t=t_{i-1}$ ;  $s_{x\_GPS,i,i-1}$  – passed distance during time period  $[t_{i-1} \ t_i]$  measurement.

Rule of intelligent algorithm applied to passed distance measurements is following:

– if  $a_x > \gamma$  at time  $t=t_{i-3}, t_{i-2}, t_{i-1}$ , then

$$s_{x\_GPS,i} = s_{x\_GPS,i-1} + s_{x\_GPS,i,i-1}, \quad (3)$$

– if  $a_x \leq \gamma$  at time  $t=t_{i-3}, t_{i-2}, t_{i-1}$ , then

$$s_{x\_GPS,i} = s_{x\_GPS,i-1} + 0, \quad (4)$$

where  $a_x$  – estimated accelerometer signal;  $\gamma$  – empirical coefficient;  $s_{x\_GPS,i}$  – passed distance value at time  $t=t_i$ ;  $s_{x\_GPS,i-1}$  – passed distance value at time  $t=t_{i-1}$ ;  $s_{x\_GPS,i,i-1}$  – passed distance during time period  $[t_{i-1} \ t_i]$ .

This rule was defined experimentally through analyse of accelerometer signals, measured by sensor during different modes of vehicle movement and values of passed distance measured by DigiRoller Plus II. The main idea of this rule is to exclude distance increasing due to the uncertainty of GPS measurements and uncompensated measurement noise of accelerometer.

Experiments show that the value of  $\gamma$  depends on the dynamic mode of vehicle movement. Having information about passed distance value measured by DigiRoller Plus II, it's possible to estimate optimal values of  $\gamma$  (when the distance estimation error approaches to minimum) and find relationship between the vehicle movement dynamic and value of  $\gamma$ . The distance estimation error in Fig.6,7 was calculated as difference between distance value measured by DigiRoller Plus II and estimations obtained by IKF using different values of parameter  $\gamma$ .

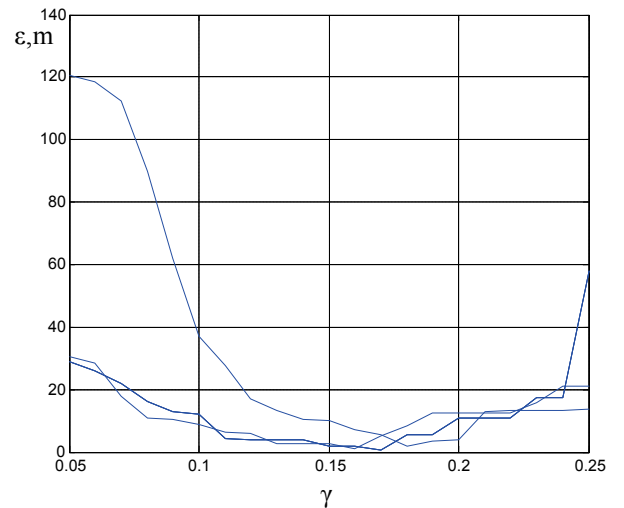


Fig. 6. Distance estimation error versus  $\gamma$

The distance estimation error function versus value of parameter  $\gamma$  for the case of moderate dynamic mode of vehicle movement (velocities up to 90km/h) are presented in the Fig.6. There're conducted three tests with high dynamic and we see that optimal values of parameter  $\gamma$  are almost the same for these three tests:  $\gamma = [0.16 \dots 0.18]$ . The estimation error function versus value of parameter  $\gamma$

for the case of low dynamic mode of vehicle movement (velocities up to 50 km/h) are presented in the Fig.7. There're conducted two tests and we see that optimal values of parameter  $\gamma$  are almost the same  $\gamma = [0.04 \dots 0.05]$ . These results are very important as give us quite narrow range of optimal  $\gamma$  to be used in developed algorithm in order to obtain reliable distance estimation for different types of vehicle movement.

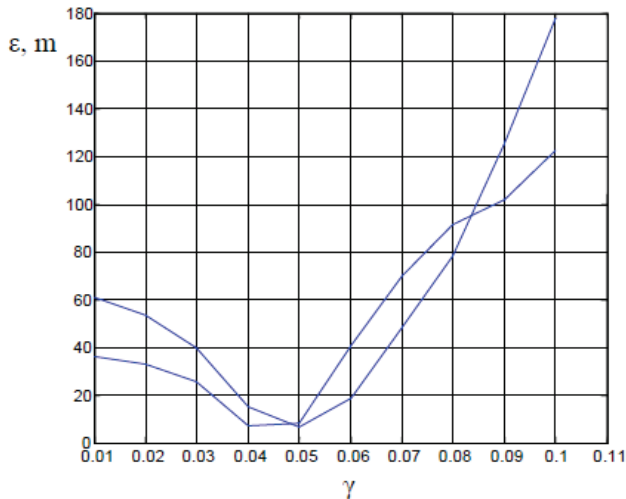


Fig. 7. Distance estimation error versus  $\gamma$

### Experiments results

The experiments were conducted for different vehicle movement velocities: 40 km/h, 80km/h and for two types of road: road with asphalt covering and earth road. The reference value of distance was obtained by measuring wheel (see Table 1) and the passed distance by vehicle was always the same and equal 1005m.

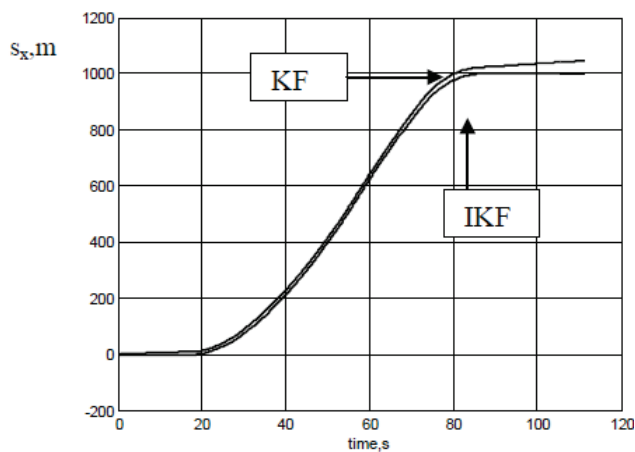


Fig. 8. Passed distance estimation curves versus time

The value of parameter  $\gamma$  was chosen according recommendations in the previous section. For the tests with high dynamic mode of moving vehicle, the parameter  $\gamma = 0.17$  and in case of low dynamic mode of moving vehicle, the parameter  $\gamma = 0.05$ . The passed distance estimations during time period  $[t_1 \ t_2]$  are shown in the Fig.8-10. For simplicity we assume that  $t_1=0s$ .

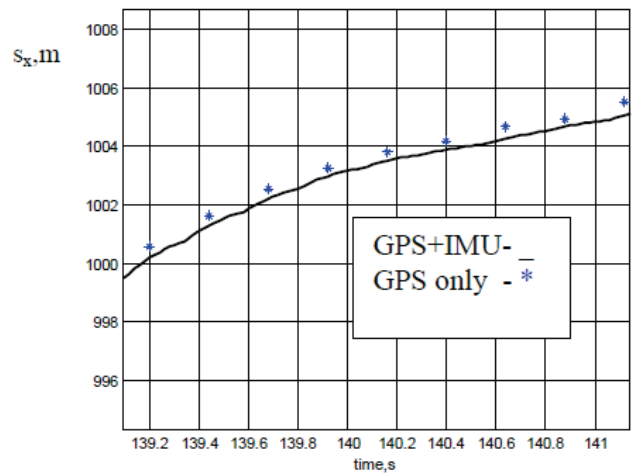


Fig. 9. Passed distance estimation curves versus time

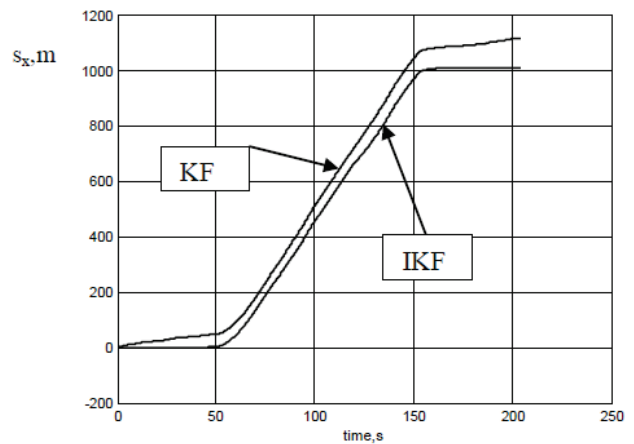


Fig. 10. Passed distance estimation curves versus time

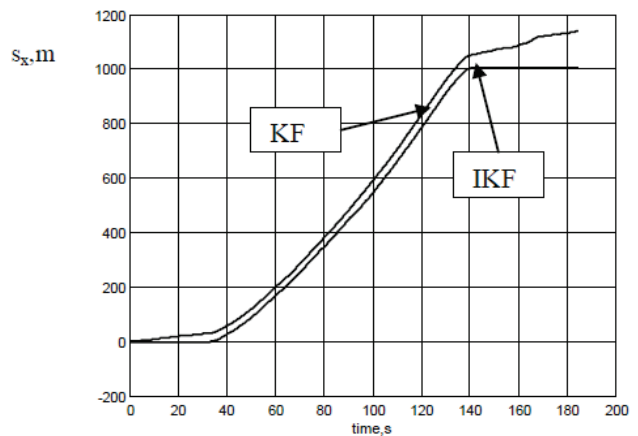


Fig. 11. Passed distance estimation curves versus time

The passed distance estimation in Fig. 8 is given for the case when the maximum vehicle velocity was 86 km/h and on asphalt road. Passed distance estimations obtained using IMU and GPS data (zoomed in from Fig.8) and measured distance (according only raw GPS measurements), which is preprocessed by intelligent algorithm are shown in Fig. 9. The passed distance estimation in Fig. 10 is given for the case when the maximum vehicle velocity was 40 km/h and on earth road. The passed distance estimation in Fig. 11 is given for the

case when the maximum vehicle velocity was 50 km/h and on asphalt road.

These estimations of distance are obtained by sensor measurement data processing with simple linear Kalman filter (KF) and by intelligent Kalman filter (IKF).

The distance estimation error (comparing with made distance measurements by measuring wheel) are given in Table 2. From Table 2 we see that in case of ordinary Kalman filter there's considerable estimation error of passed distance. This error is mainly due to the uncertainty of GPS measurements at stationary mode.

In order to check IKF algorithm functionality additional experiments were conducted. The vehicle passed distance with one and two short stops. The passed distance value was 1005 m. As the velocity The estimated curves for passed distance versus time is shown in Fig. 12, 13. From Fig. 12, 13 we see visually that IKF algorithm has better estimation of passed distance value.

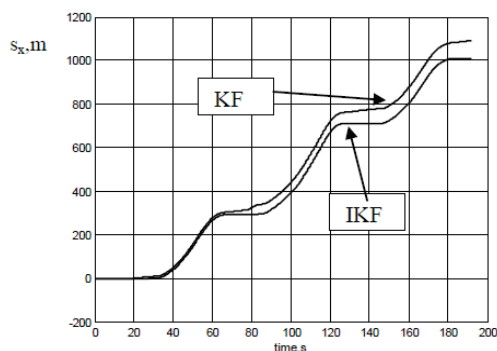


Fig. 12. Passed distance estimation curves versus time

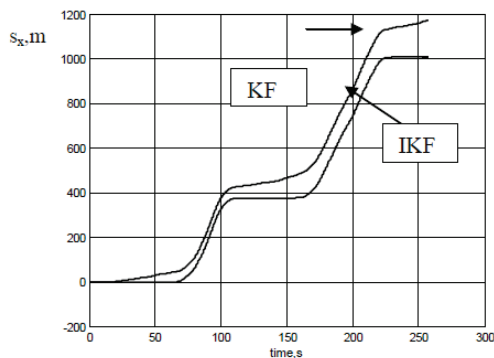


Fig. 13. Passed distance estimation curves versus time

Table 2. Passed distance estimation error for KF and IKF algorithm

Test #	Distance estimation error, m		Test description (velocity, road)
	KF	IKF	
1	38	9	40 km/h , earth road
2	21	5	50 km/h, asphalt road
3	22	6	40 km/h, asphalt road
4	15	6	80-90 km/h, asphalt road

Test #	Distance estimation error, m		Test description (velocity, road)
	KF	IKF	
5	20	5	80-90 km/h, asphalt road
6	21	1	80-90 km/h, asphalt road

## Conclusions

It was shown that developed IKF algorithm is able to estimate passed distance with better accuracy, comparing with standard Kalman filter. It's necessary to set optimal value of parameter  $\gamma$ , in order to have minimum of passed distance estimation error. The task of  $\gamma$  optimal value determining is not straightforward. But during conducted experiments it was possible to find optimal parameters values for the cases of low and high dynamics of vehicle movement. One of developed algorithm (1-4) advantages is convenience of it utilization: for passed distance value estimation we need only results of raw acceleration and raw position (latitude, longitude, height) measurements from sensors, to choose appropriate value of parameter  $\gamma$  according to the type of vehicle movement mode and to set appropriate system noise level to have accelerometer signal bias estimation. Usually the last value can be predefined in Kalman algorithm by designer and there no need for user to solve this problem.

## Acknowledgements



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**V. Bistrovs, A. Kluga. Distance Estimation using Intelligent Fusion of Navigation Data // Electronics and Electrical Engineering. – Kaunas: Technologija, 2010. – No. 5(101). – P. 47–52.**

INS/GPS navigation has changed due to advances in inertial manufacturing technology. This has created sensors (accelerometers, gyroscopes, magnetometers) that can be packaged with a GPS receiver/antenna for everyday use. These new manufacturing technologies are creating inertial sensors such as MEMS inertial sensors that are smaller and consume less power, but they also exhibit much larger errors comparing with their higher priced units. Kalman filtering is the main technique for combined IMU/GPS sensor data processing. Intelligent algorithm application for sensor data fusing is one of the newest areas of research. In the current paper the simplified intelligent algorithm is developed for GPS and accelerometer data combined processing. The performance of developed algorithm was checked through made experiments for estimation of distance passed by vehicle. The compare of passed distance estimation error for standard and intelligent Kalman algorithm are presented in the paper. Presented intelligent Kalman algorithm has smaller estimation error, simple in use and not demanding for computing power. Ill. 13, bibl. 5, tabl. 2 (in English; abstracts in English, Russian and Lithuanian).

**В. Быстров, А. Клуга. Определение расстояния используя интеллектуальный алгоритм совместной обработки навигационной информации // Электроника и электротехника. – Каунас: Технология, 2010. – № 5(101). – С. 47–52.**

Методы INS/GPS навигации изменились в связи с достижениями в производстве инерционных сенсоров. В результате появились сенсоры (акселерометры, гироскопы, магнетометры) которые размещаются совместно с GPS приемником и антенной. Новые технологии позволили создать инерционные сенсоры, такие, например как MEMS сенсоры, которые меньше по размерам и потребляют меньшую мощность, но им присущи большие ошибки по сравнению с их более дорогими аналогами. Фильтр Калмана является главным алгоритмом совместной обработки данных от IMU/GPS сенсоров. Применение интеллектуальных алгоритмов совместной обработки IMU/GPS данных является новой областью исследований. В данной статье представлен разработанный интеллектуальный алгоритм Калмана. Работоспособность алгоритма была проверена экспериментально для оценки пути пройденного, автомобилем. Сравнение ошибки оценки пройденного пути для стандартного и интеллектуального алгоритма приведено в данной статье. Разработанный алгоритм имеет меньшую ошибку оценки, прост в использовании и не требователен к вычислительной мощности. Ил. 13, библи. 5, табл. 2 (на английском языке; рефераты на английском, русском и литовско яз.).

**V. Bistrovs, A. Kluga. Vietos paieškos intelektualusis algoritmas navigacinei informacijai apdoroti // Elektronika ir elektrotechnika. – Kaunas: Technologija, 2010. – Nr. 5(101). – P. 47–52.**

Aprašomi įvairūs jutikliai (akceleratoriai, giroskopai, magnetometrai), naudojami GPS imtuvuose ir antenose. Šių jutiklių kokybei pagerinti pasiūlyta nauja technologija. Išanalizuotas Kalmano filtro algoritmas, kuris labai pagerina IMU/GPS jutiklių savybes. Remiantis šių tyrimų duomenimis, sukurtas intelektualusis Kalmano algoritmas, kurio naujumas ir originalumas patikrintas, įvertinant automobilių nuvažiuotą kelią. Įrodyta, kad įvertinimo paklaida yra minimali. Il. 13, bibl. 5, lent. 2 (anglų kalba; santraukos anglų, rusų ir lietuvių k.).