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Использование обобщённой регрессионной нейронной сети для повышения точности автономной навигации в условиях неустойчивого приёма сигналов систем глобального позиционирования

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Аннотация. Автономная навигация играет важную роль во многих областях и приложениях, в значительной степени опираясь на измерения Глобальной системы позиционирования (ГПС), которая в некоторых районах может быть недоступна. Это напрямую влияет на работу автономной навигации, что, в свою очередь, приводит к проблемам, связанным с её функциями. В данном исследовании использована обобщённая регрессионная нейронная сеть (ОРНС или GRNN), являющаяся вариацией радиально-базисных нейронных сетей, для компенсации измерений ГПС в условиях её отсутствия с целью повышения точности параметров автономной навигации (в первую очередь положения и скорости) объекта. ОРНС интегрирована со слабо связанной обобщённой фильтрацией Калмана (ОФК). Были оценены параметры положения, скорости, ориентации и смещения сенсоров. Оценка предложенного метода проводилась с использованием набора данных из интернета. Были созданы две симуляции отсутствия измерений ГПС (периоды отсутствия составили 40 и 30 с) для оценки поведения ОРНС. Результаты показали, что использование ОРНС в условиях отсутствия ГПС является эффективным и надёжным решением, превосходящим метод слабо связанного ОФК.

Ключевые слова: *автономная навигация, глобальная система позиционирования, обобщённая регрессионная нейронная сеть, слабо связанная обобщённая фильтрация Калмана.*

Using a generalized regression neural network to improve the accuracy of autonomous navigation in conditions of unstable reception of global positioning system signals

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Abstract. Autonomous navigation is very important in many fields and applications and it specifically depends on global positioning system (GPS) measurements which may not be accessible in some areas. This will directly affect the autonomous navigation and sequentially this will lead to problems according to the function of autonomous navigation. In this research, generalized regression neural network (GRNN) which is a variation to radial basis neural networks, was used to compensate global positioning system (GPS) measurements in case of GPS absences to increase accuracy of autonomous navigation parameters (basically location and velocity) of object. GRNN is integrated with loosely coupled Extended Kalman Filter (EKF). Location, velocity, orientation parameters and biases of sensors are estimated. The evaluation of this methods was conducted using dataset from Internet, two simulations for the GPS measurements outages were made (first outage periods were 35 and 60 seconds) to evaluate the behavior of GRNN, the results shows that using GRNN in GPS absence is effective and robust, it outperformed the only loosely coupled EKF method.

Keywords: Autonomous Navigation, Global positioning System, generalized regression neural network, Loosely Coupled Extended Kalman Filter (EKF).

Introduction

In the field of application of artificial intelligence (AI) methods in various fields of applied sciences, many AI technologies have been developed and applied for autonomous navigation of mobile objects. This integration is extremely effective because the main task of autonomous navigation is to calculate navigation parameters of mobile objects, such as location (position) and speed at each moment in time. The basis of autonomous navigation is data from inertial sensors such as accelerometers and gyroscopes, which make up inertial navigation systems (INS). Data from the Global Positioning System (GPS) and other sensors such as odometers and vision sensors can also be used [1; 2]. GPS data contains location and velocity information, but it has a number of disadvantages: GPS signals are sometimes unavailable in some environments; signal interference may occur in important locations; signal delays or low frequency may limit GPS accuracy; vulnerability to signal spoofing and jamming; dependence on satellite infrastructure, limited functionality indoors and in other environments [3]. To overcome these shortcomings, the integration of GPS data with inertial sensors was developed. Such integration can be implemented in the form of an extended Kalman filter (EKF), and other approaches. A loosely coupled integration methodology using EKF has been implemented between GPS, accelerometers and gyroscopes [4]. This approach is called GPS/INS integration. It provides reliable calculation of navigation parameters in cases where GPS signals are delayed for a certain period of time. However, if this period is too long, the integration may produce inaccurate calculations. Moreover, inertial sensors have a number of disadvantages, such as offset, scale error, installation error, and other.

Generalized regression neural network (GRNN)) is a variation of radial basis neural networks. GRNN was developed by D. F. Specht in 1991. It can be used for regression, prediction and classification, and also serves as a good solution for online dynamic systems. GRNN is an advanced neural network technique based on radial basis functions with a non-iterative parameter estimation procedure. Although it cannot be strictly classified as a nonparametric method, due to its flexibility in approximating complex dependencies, it exhibits characteristics inherent in such approaches [5; 6].

The main objective of the article is to use a generalized regression neural network (GRNN) to improve the performance of the GPS/INS system in conditions of GPS signal outages, as well as their absence or interruptions.

Literature Review

GRNN has not been previously applied in this area, although neural networks in general have been actively used. For example, in [7] the authors applied a stable extended Kalman filter (SEKF) to overcome the low accuracy of the GPS/INS algorithm during GPS outages. They developed a low-cost method for GPS/INS integration and compensation of algorithm errors in the absence of GPS signals. Their approach compensated for the impact of gross errors in INS observations by using an artificial neural network-based integration method to fill in missing position information. A well-trained neural network predicted and compensated for errors in interrupted position signals. The effectiveness of the proposed method was assessed in field tests using specially developed equipment, GPS and INS sensors. The results showed a 67% improvement in positioning accuracy for each axis in the outage periods. The proposed algorithm is capable of improving the accuracy of the integrated GPS/INS system to meet navigation requirements.

[8] proposed a new approach to autonomous navigation of drones along pre-defined routes using only visual data from the on-board camera, without relying on GPS. The method is based on a deep convolutional neural network (CNN) combined with a regressor to generate control commands for the drone. To increase the adaptability of the system to real conditions, additional auxiliary navigation paths were used, forming a "navigation corridor" to increase the volume of data. The proposed algorithm replaces a human operator, improves the accuracy of GPS-based map navigation, eliminates problems associated with the substitution of GPS signals, and allows navigation in conditions without GPS signals. The approach was tested in two scenarios using the Unreal Engine-based drone simulator AirSim. The results were promising: the average lateral deviation was less than 1.4 m, and the minimum distance to the control points was less than 1 m.

Several studies have applied AI methods in the field of navigation, including adaptive neuro-fuzzy inference system (ANFIS) in [9], radial basis neural networks (RBNN) in [10; 11].

GRNN was also used in navigation systems. For example, in [12] it was used to fill missing values in datasets for data analysis and machine learning. GRNN takes into account the relationships between data better than statistical methods such as using means or medians. GRNN has been proven to be more effective than statistical methods, especially on large datasets. This research demonstrates using GRNN to compensate for GPS signals when they are delayed or absent for various reasons.

Methods

The system description

The orientation of a mobile object can be described using Euler angles or quaternions. The main advantage of using quaternions is the linearity of kinematic equations in the quaternion representation, as well as the absence of singularities [13]. The state vector x in the EKF contains orientation parameters (quaternions), the object's location (LlA: latitude, longitude, altitude), the object's velocity (V_{ned}: North, East, Down), as well as the gyroscope and accelerometer offsets. The Kalman filter consists of two main phases: prediction and correction. The prediction phase uses information about previous values of the state vector to make an a priori estimate of the new state vector. The correction phase uses GPS signal measurements to correct the state vector. A complete description of the system equations and EKF is presented in [14].

Integration of GPS/INS and GRNN

GPS/INS integration is performed at every sampling cycle. When GPS signals are present, position and velocity information is obtained from the GPS data and used in the EKF correction phase. Let the frequency of data from GPS be $R_{GPS,}$ and the frequency of data from accelerometers and gyroscopes is R_{ag}. Since R_{ag} is greater than R_{GPS}, the prediction phase of the Kalman filter will be executed more often than the correction phase. If the GPS signal is delayed, the integration error will accumulate, leading to an increase in the error in determining the navigation parameters.

GRNN is used in the correction phase if GPS data are not available. In the presence of a GPS signal, the GRNN is trained and updates its parameters. Fig. 1 shows the complete integration scheme.

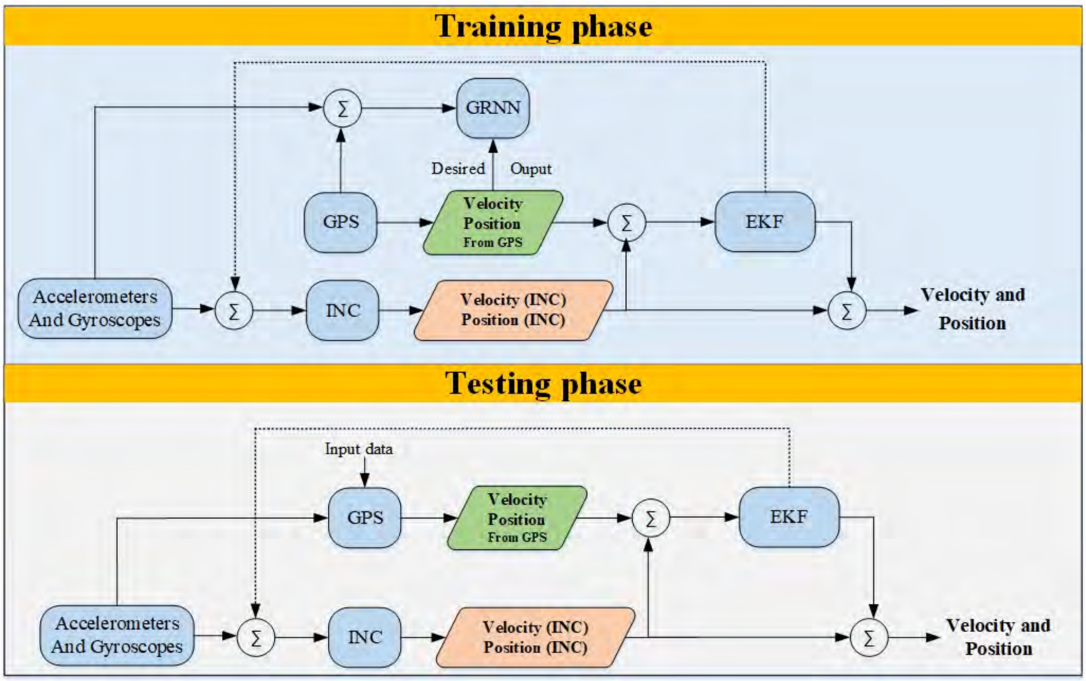

Рис. 1. Схема сочетания ГПС/ИНС и ОРНС

Fig. 1. Flowchart of combination GPS/INS and GRNN

During the training phase, the GRNN uses input data and required output values obtained from available GPS measurements. It results in a trained GRNN model that, in the absence of GPS measurements, is used to estimate the measurements to compensate for the unavailability of GPS.

GRNN

GRNN is a one-way artificial neural network model consisting of four layers: input layer, sample layer, adder layer, and output layer. Unlike a backpropagation AI network, iterative training is not required. Each layer of the structure contains a different number of neurons and is connected sequentially to the next layer [15]:

– the first layer is the input layer. The number of neurons in this layer corresponds to the number of data characteristics;

– sample layer. The number of neurons is equal to the number of data in the training set. The neurons of this layer calculate the distances between the training data and the test data. The obtained results are passed through a radial basis function (activation function) with parameter σ, after which the values of the weights are determined;

– the summatory layer consists of two parts: the numerator and the denominator. The numerator includes the sum of the products of the training outputs and the activation function results (weights). The denominator is the sum of all weight values. This layer passes the numerator and denominator to the next output layer;

– output layer. It Contains one neuron that computes the output value by dividing the numerator of the summatory layer by its denominator.

GRNN mathematical equation is as follows:

$$Y(x) = \frac{\sum_{k=1}^{N} y_k K(x, x_k)}{\sum_{k=1}^{N} K(x, x_k)}, \tag{1}$$

Where $Y(x)$ is the predicted value for the input data (in our case, Y is a vector of six components: three are for location and three – for velocity; y_k is the activation weight for the template layer neuron at the k-th cycle; $K(x, x_k)$

$$K(x, x_k) = K_k = e^{-\frac{d_k}{2\sigma^2}}, \tag{2}$$

$$d_k = (x - x_k)^T (x - x_k), \tag{3}$$

where d_k – is the square of the Euclidean distance between the training samples x_k and the input data x.

$$Y(x) = \frac{\sum_{k=1}^{N} y_k W_k}{\sum_{k=1}^{N} W_k},$$

$$W_k = e^{-\frac{(x - x_v)^2}{2\sigma^2}}$$

The parameter σ determines how much the weights W_k differ. If σ is big, all W_k becomes approximately equal and the expression approaches the usual mean y_k. If σ is small, the sum will be strongly influenced by the terms with the biggest d_k, which will change the result. Parameter σ has an impact on the weight of each term in the sum. If σ is changed, the relative importance of the different y_k will change, it will lead to a different result. Therefore, σ plays a key role in the expression and cannot be excluded.

At the k-th cycle x_k contains:

– 3 accelerometer data components (at cycles $k, k-1, k-2, k-3$);

– 3 gyroscope data components (at cycles $k, k-1, k-2, k-3$);

– 3 velocity data components (at cycles $k-1, k-2, k-3, k-4$);

– 3 coordinate components LlA (at cycles $k-1, k-2, k-3, k-4$).

The total input size is 12 × 4 = 48.

At the training stage, the output data contains:

– 3 velocity components (at cycle k);

– 3 coordinate components LlA (at cycle k).

The total output size is 6. Figure 2 presents GRNN structure.

Dataset

The dataset contains all the necessary information, including data from accelerometers, gyroscopes and GPS. The GPS data rate is 10 Hz, and the accelerometer and gyroscope data rate is 100 Hz.

Research findings

To evaluate and simulate the absence of the GPS signal, two signal interruption periods were created on two different cycles with different durations: the first interruption lasted 40 s, and the second lasted 30 s. This dataset does not contain any altitude variations. The total experiment time is 760 s. The results of the experiment are presented in Fig. 3–6.

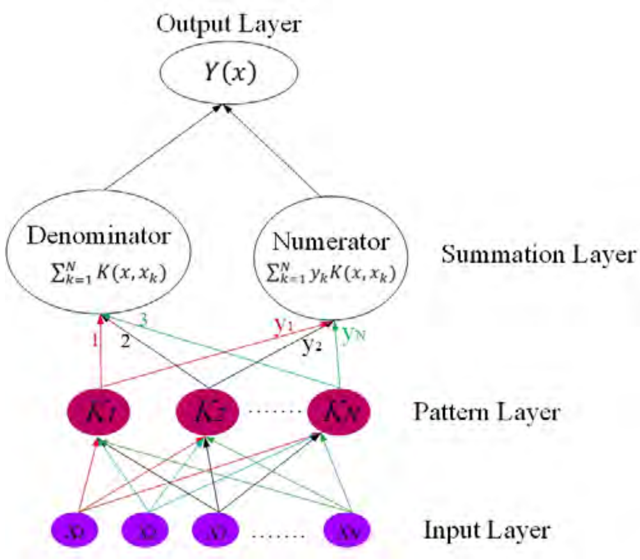

Рис. 2. Общая структура ОРНС

Fig. 2. General structure of GRNN

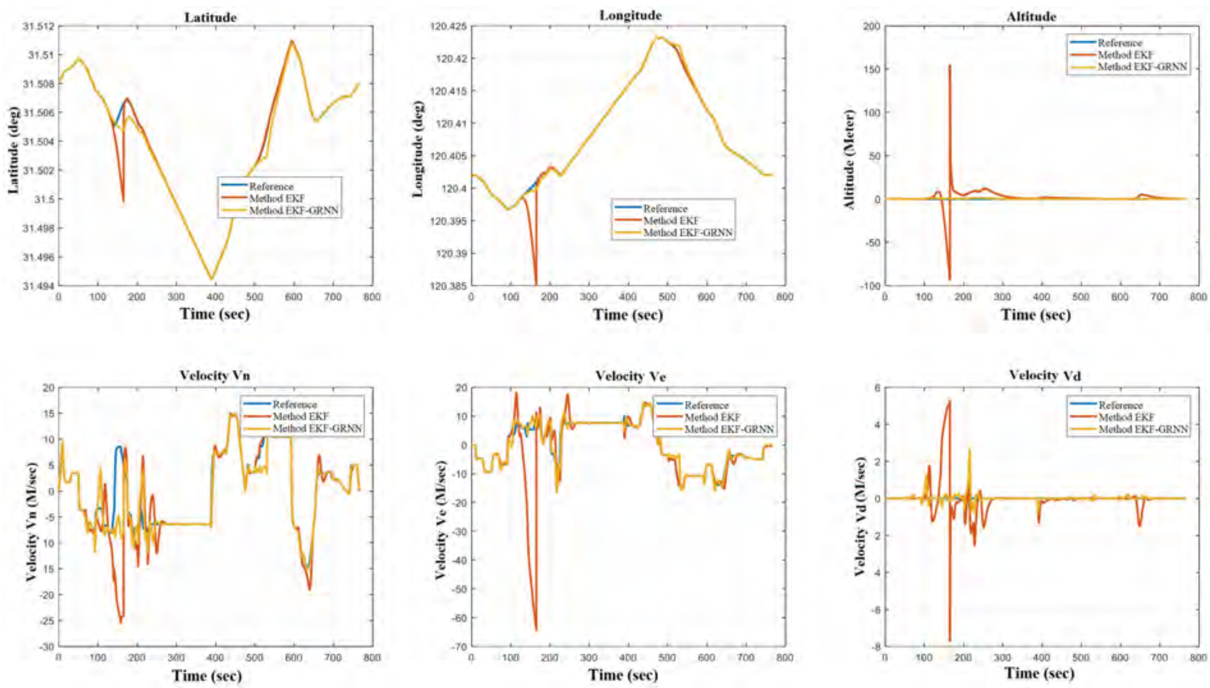

Рис. 3. LlA и скорость

Fig. 3. LlA and velocity

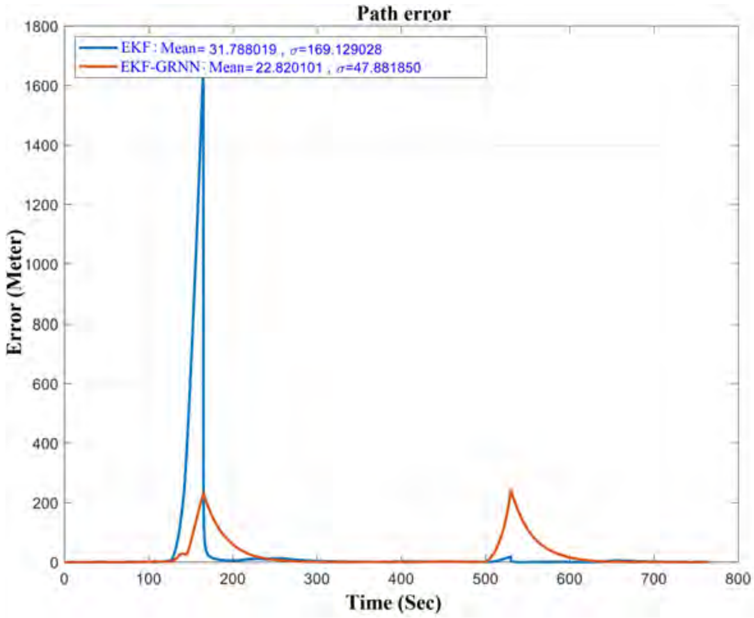

Рис. 4. Горизонтальная ошибка пути

Fig. 4. Horizontal path error

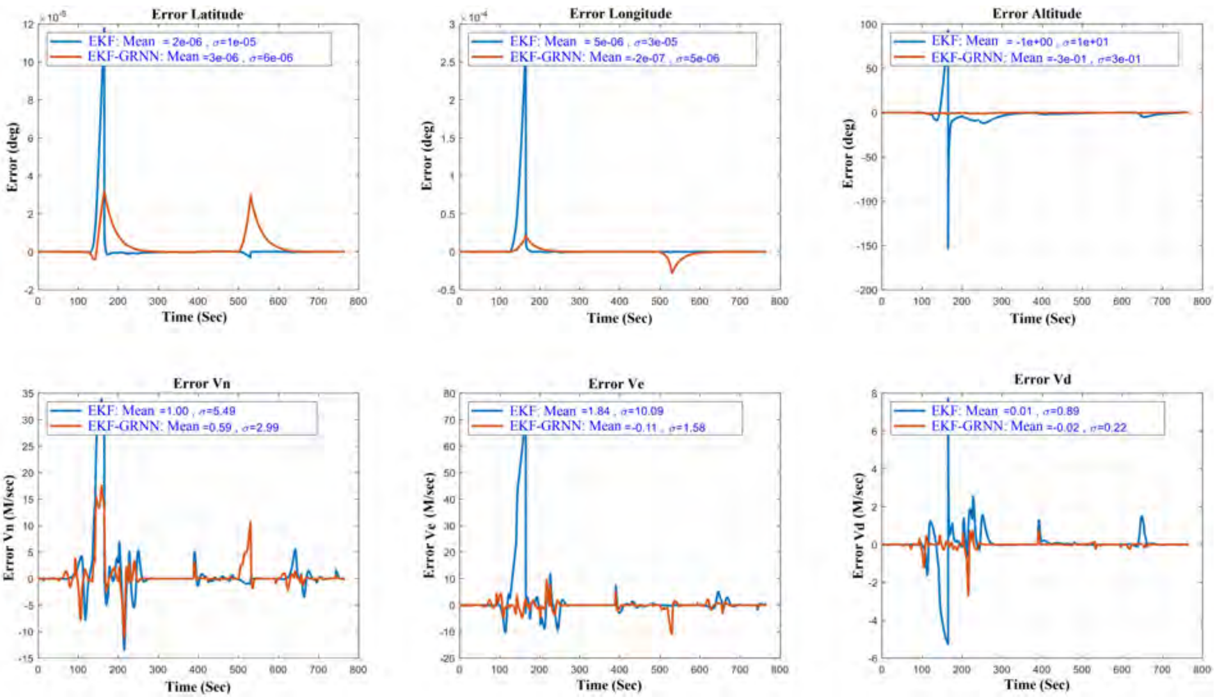

Рис. 5. Ошибка в *LlA* и скорости

Fig. 5. Error of *LlA* and velocity

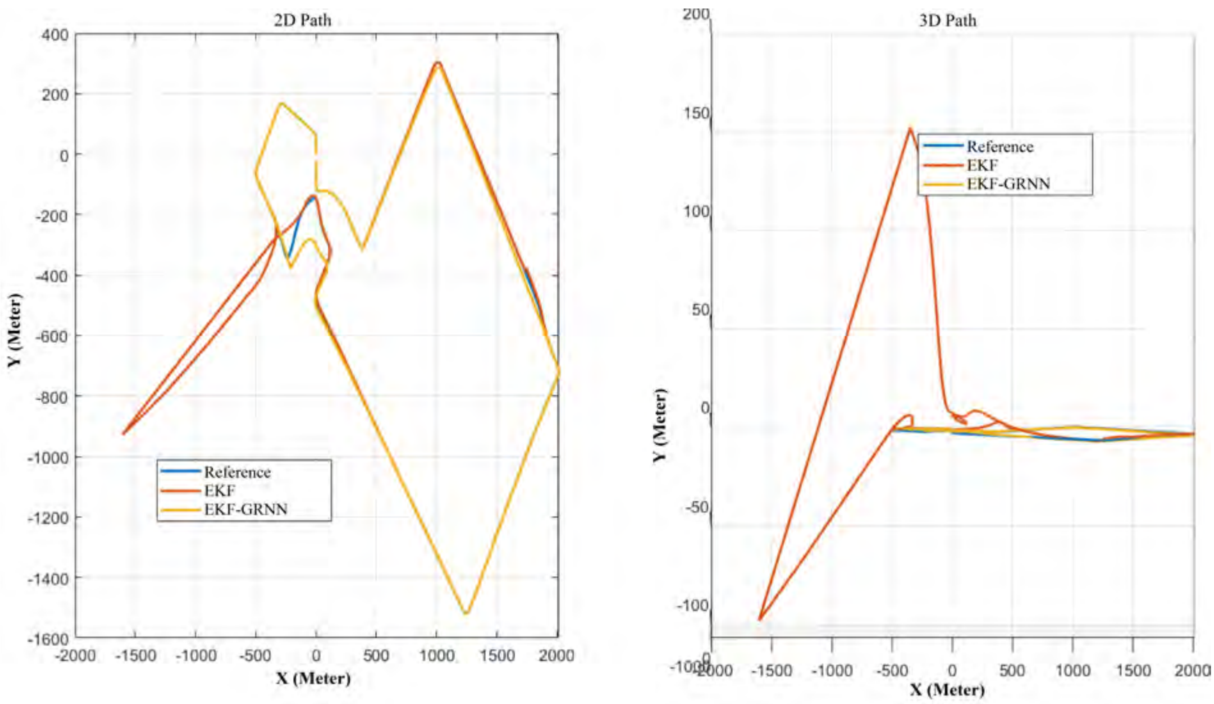

Рис. 6. Путь

Fig. 6. The path

The table shows the numerical comparison of the results.

Comparison of the results

	The first dataset			
Parameter	Error	EKF	EKF-GRNN	Improvement, %
Height (m)	Average	1	0,3	70
	RMSD	10	0,3	97
V_n (m/s)	Average	1	0,59	41
	RMSD	5,49	2,99	45,53
V_e (m/s)	Average	1,84	0,11	94,14
	RMSD	10,09	1,58	84,34
V_d (m/s)	Average	0,01	0,02	–
	RMSD	1,89	0,22	88,35
Horizontal error (M)	Average	31,78	22,82	28,19
	RMSD	169,13	47,88	71,69

Note. RMSD – root mean square deviation.

Discussion

Taking advantage of the GRNN training procedure allows to determine the optimal value of the parameter σ. The best practice is to find the value at which the mean square error (MSE) is minimal. Training is performed using the input data to find σ corresponding to the minimum MSE value. The results show that the GRNN-EKF method is superior to the method using only EKF, and the accuracy of determining navigation parameters is significantly improved. This performance improvement is due to the main advantages of the estimation performed by GRNN, which are always able to converge to a global solution and do not get stuck in a local minimum, unlike standard feedforward networks trained using backpropagation.

In addition, the input data contains features based on previous values of the target data (this means previous LlA values and velocities), as well as inertial measurement data of the object, which directly influence the target output values of GRNN. This allows GRNN to model nonlinear dependencies between input data and target output data. GRNN also has got the ability to speed up the learning process, permitting the network to learn faster. GRNN is trained using a one-pass method, taking only a fraction of the time required to train standard feedforward networks using the backpropagation method. The parameter σ, called Spread, is the only free parameter in the network, which is often determined by cross-validation in various applications of GRNN.

Application areas of the results include target tracking, surveillance of inaccessible areas and information gathering.

Conclusion

The research demonstrated that using a generalized regression neural network (GRNN) to compensate for missing GPS data effectively improves the accuracy of autonomous navigation parameters such as position and speed. The integration of GRNN with loosely coupled Kalman filtering showed robust results, outperforming the traditional EKF-only approach. This is confirmed by the successful simulation of the absence of GPS data, which makes the proposed method promising for application in conditions of the absence or delay of GPS signals.

Data availability: The information is presented as raw data and true calibration parameters (https://github.com/Shelfcol/gps_imu_fusion/tree/main)

Библиографические ссылки

1. Braasch M. S. Inertial navigation systems // Aerospace Navigation Systems. 2016. P. 1–25. Doi: 10.1002/9781119163060.ch1

2. Jekeli C. Inertial navigation systems with geodetic applications. Walter de Gruyter GmbH & Co KG. 2023.

3. Phelts R. E., Akos D. M. Nominal signal deformations: limits on GPS range accuracy // The 2004 International Symposium on GNSS/GPS. 2004. Vol. 6. P. 8.

4. Gui P., Tang L., Mukhopadhyay S. MEMS based IMU for tilting measurement: Comparison of complementary and kalman filter based data fusion // 2015 IEEE 10th conference on Industrial Electronics and Applications (ICIEA). IEEE, 2015. P. 2004–2009.

5. A general regression neural network / D. F. Specht et al. // IEEE transaction on neural networks. 1991. Vol. 2, No. 6. P. 568–576.

6. New methods based on a genetic algorithm back propagation (GABP) neural network and general regression neural network (GRNN) for predicting the occurrence of trihalomethanes in tap water / K. Liu et al. // Science of the Total Environment. 2023. Vol. 870. P. 161976.

7. Aslinezhad M., Malekijavan A., Abbasi P. ANN-assisted robust GPS/INS information fusion to bridge GPS outage // EURASIP Journal on Wireless Communications and Networking. 2020. Vol. 2020, No. 1. P. 129.

8. Deep convolutional neural network based autonomous drone navigation / K. Amer et al. // Thirteenth International Conference on Machine Vision. SPIE. 2021. Vol. 11605. P. 16–24.

9. INS error estimation based on an ANFIS and its application in complex and covert surroundings / Y. Duan et al. // ISPRS International Journal of Geo-Information. 2021. Vol. 10, No. 6. P. 388.

10. Online INS/GPS integration with a radial basis function neural network / R. Sharaf et al. // IEEE Aerospace and Electronic Systems Magazine. 2005. Vol. 20, No. 3. P. 8–14.

11. Research on Integrated Navigation Algorithm Based on Radial Basis Function Neural Network / H. Liu et al. // Journal of Physics: Conference Series. IOP Publishing, 2021. Vol. 1961, No. 1. P. 012031.

12. Татарникова Т. М., Боженко В. В. Основные принципы работы обобщенной регрессионной нейронной сети при заполнении пропущенных значений в наборах данных // Продукты и системы. Т. 37, № 3. С. 364–368.

13. Representing attitude: Euler angles, unit quaternions, and rotation vectors / et al. Diebel J. // Matrix. 2006. Vol. 58, No. 15–16. P. 1–35.

14. Crassidis J. L. Sigma-point Kalman filtering for integrated GPS and inertial navigation // IEEE Transactions on Aerospace and Electronic Systems. 2006. Vol. 42, No. 2. P. 750–756.

15. Ghritlahre H. K., Prasad R. K. Exergetic performance prediction of solar air heater using MLP, GRNN and RBF models of artificial neural network technique // Journal of environmental management. 2018. Vol. 223. P. 566–575.

References

1. Braasch M. S. Inertial navigation systems. *Aerospace Navigation Systems*. 2016, P. 1–25. Doi: 10.1002/9781119163060.ch1

2. Jekeli C. Inertial navigation systems with geodetic applications. *Walter de Gruyter GmbH & Co KG*. 2023.

3. Phelts R. E., Akos D. M. Nominal signal deformations: limits on GPS range accuracy. *The 2004 International Symposium on GNSS/GPS*. 2004. Vol. 6. P. 8.

4. Gui P., Tang L., Mukhopadhyay S. MEMS based IMU for tilting measurement: Comparison of complementary and kalman filter based data fusion. *2015 IEEE 10th conference on Industrial Electronics and Applications (ICIEA)*. IEEE, 2015. P. 2004–2009.

5. Specht D. F. et al. A general regression neural network. *IEEE transaction on neural networks*. 1991, Vol. 2, No. 6, P. 568–576.

6. Liu K. et al. New methods based on a genetic algorithm back propagation (GABP) neural network and general regression neural network (GRNN) for predicting the occurrence of trihalomethanes in tap water. *Science of the Total Environment.* 2023, Vol. 870, P. 161976.

7. Aslinezhad M., Malekijavan A., Abbasi P. ANN-assisted robust GPS/INS information fusion to bridge GPS outage. *EURASIP Journal on Wireless Communications and Networking*. 2020, Vol. 2020, No. 1, P. 129.

8. Amer K. et al. Deep convolutional neural network based autonomous drone navigation. *Thirteenth International Conference on Machine Vision. SPIE*. 2021, Vol. 11605, P. 16–24.

9. Duan Y. et al. INS error estimation based on an ANFIS and its application in complex and covert surroundings. *ISPRS International Journal of Geo-Information*. 2021, Vol. 10, No. 6, P. 388.

10. Sharaf R. et al. Online INS/GPS integration with a radial basis function neural network. *IEEE Aerospace and Electronic Systems Magazine*. 2005, Vol. 20, No. 3, P. 8–14.

11. Liu H. et al. Research on Integrated Navigation Algorithm Based on Radial Basis Function Neural Network. *Journal of Physics: Conference Series*. IOP Publishing, 2021, Vol. 1961, No. 1, P. 012031.

12. Tatarnikova, T.M., Bozhenko, V.V. [Basic principles of generalized regression neural network for filling missing values in data sets]. *Software & Systems.* Vol. 37, No. 3, P. 364–368 (In Russ.).

13. Diebel J. et al. Representing attitude: Euler angles, unit quaternions, and rotation vectors. *Matrix.* 2006, Vol. 58, No. 15–16, P. 1–35.

14. Crassidis J. L. Sigma-point Kalman filtering for integrated GPS and inertial navigation. *IEEE Transactions on Aerospace and Electronic Systems*. 2006, Vol. 42, No. 2, P. 750–756.

15. Ghritlahre H. K., Prasad R. K. Exergetic performance prediction of solar air heater using MLP, GRNN and RBF models of artificial neural network technique. *Journal of environmental management*. 2018, Vol. 223, P. 566–575.

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