UDC 004.85:629.05
DOI: 10.15587/2706-5448.2021.225282
Article type «Reports on Research Projects»

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SIMULATION OF PLATFORM-FREE INERTIAL NAVIGATION SYSTEM OF UNMANNED AERIAL VEHICLES BASED ON NEURAL NETWORK ALGORITHMS

The object of research is the process of controlling the trajectory of unmanned aerial vehicles (UAVs) in autonomous flight mode based on neural network algorithms. The study is based on the application of numerical-analytical approach to the selection of modern technical solutions for the construction of standard models of platformless inertial navigation systems (BINS) for micro and small UAVs, followed by support for assumptions. The results of simulation in the Matlab environment allowed to simulate the operation of the UAV control system based on MEMS technology (using microelectromechanical systems) and Arduino microcomputers. It was also possible to experimentally determine the nature of the influence of the structure of the selected neural network on the process of formation of navigation data during the disappearance of the GPS signal. Thus, to evaluate the effectiveness of the proposed solutions for the construction of BINS, a comparative analysis of the application of two algorithms ELM (Extreme Learning Machine)-Kalman and WANN (Wavelet Artificial Neural Network)-RNN (Recurrent Neural Network)-Madgwick in the form of two experiments. The purpose of the experiments was to determine: the study of the influence of the number of neurons of the latent level of the neural network on the accuracy of approximation of navigation data; determining the speed of the process of adaptive learning of neural network algorithms BINS UAV. The results of the experiments showed that the application of the algorithm based on ELM-Kalman provides better accuracy of learning the BINS neural network compared to the WANN-RNN-Madgwick algorithm. However, it should be noted that the accuracy of learning improved with the number of neurons in the structure of the latent level <500, which iincreases computational complexity and increases the learning process time. This can complicate the practical implementation using micro- and small UAV equipment. In addition, thanks to the simulation, the result of the study of the application of the proposed neural network algorithms to replace the input data instead of GPS signals to the input BINS, allowed to estimate the positioning error during the disappearance of GPS signals. Also, the application of the WANN-RNN-Madgwick algorithm allows to approximate and extrapolate the input signals of navigation parameters in a dynamic environment, while the process of adaptive learning in real time.

Keywords: *neural network, flight trajectory, neural network learning accuracy, simulation, navigation data.*

Received date: 11.10.2020
Accepted date: 12.12.2020
Published date: 26.02.2021

1. Introduction

In order to expanding the spectrum of automated and automatic solutions to perform various tasks, unmanned aerial vehicles with small dimensions are increasingly used. At the same time, there is a growing need to develop the latest technical solutions to control unmanned aerial vehicles (UAVs), regardless of the presence of signals from global positioning systems [1].

It is known that the determination of the positioning data of the miniature UAV type is usually based on an integrated MEMS (microelectromechanical system) strapdown inertial navigation system based on Arduino microcomputers. Algorithms of the flight route control function during the disappearance of the signal of global satellite systems are described using methods synthesized, mostly on the basis of Kalman filtering algorithms, using data from inertial sensors and GPS module [2, 3].

It is known that inertial navigation systems based on MEMS sensors have a high sensitivity, which leads to errors in determining the course, which is [4, 5]:

$$\Delta_{\omega} \in \{0.66\ldots1.16\}^{\circ}/\text{s}.$$

Thus, as a result of the sudden disappearance of global positioning system (GSP) signals or based on MEMS sensor signals (accelerometer, gyroscope, magnetometer), it is known that the structure of the BINS MEMS sensor error model is critical for correct control of the UAV flight path [4–6]. This is due to the instability of individual components, especially during the correlation period, close to the period of disappearance of the GSP signal (from 10 to 300 s).

In addition, during the maneuvering of the UAV in a dynamic environment in autonomous flight mode requirements are imposed to the navigation system MEMS based on neural network algorithms:

– measurement error from the target trajectory $T(\Delta_{\omega UAV}) \leq \{0.012...0.18\}$ °/s [6–8];
– the learning period of the neural network $t_{lerning\ rate} \leq \{20...100\}$ s is due to the limitation – the physical memory storage of the Arduino Nano microcontroller and the establishment of the required confidence interval of the representativeness of the training sample of reference navigation parameters [7, 9];
– the speed of adaptive learning of the neural network $t_{adaptive\ learning\ rate} \leq \{0.034...0.05\}$ s, i. e. the process of learning the neural network in real time.

Failure to comply with the above requirements can lead to a deviation from the target trajectory up to 400 m per 1 km, as shown in [10].

Scientific research [11] shows an effective method of compensating for errors of MEMS sensors, however, it was found that during a UAV flight, the structure of the neural network becomes more complicated, which imposes an additional computational load on the microcomputer of the navigation system.

In [12], a method of inertial navigation based on a modified Kalman filter in combination with a neural network error inverse propagation algorithm to minimize computational load is presented. The proposed improved Kalman filter based on neural networks showed better results during in the process of calculating the estimate of navigation parameters (initial shear angle). However, the model based on the Kalman algorithm does not take into account the dependence of the SINS errors at the $m-1$ step, when the operating noise characteristics relative to the previous ones are uncertain.

The authors of [13] proposed an improved Kalman filtering method using a neural network with a radial base function to reduce the influence of the dynamic environment on the determination of the UAV trajectory after GPS signal loss. The result showed that using the proposed method it was possible to achieve a decrease in the influence of dynamic variations in the noise characteristics of the UAV SINS after the loss of the GPS signal. However, this leads to an increase in computational complexity relative to the running time.

In [14], a method for filtering a sample of the initial gyroscope data based on the genetic neural network algorithm searching the neural architecture NAS-RNN is proposed. However, the result showed that the use of NAS RNN leads to an increase in the search and learning time for the neural network structure of the navigation system, but the error of the MEMS gyroscope has decreased compared to the deviation LSTM-RNN.

For today, in the field of machine learning, the popularity of algorithms for automatic search for a model of neural network structures is growing, which makes it possible to select a neural network model as accurately as possible for solving the target problem, taking into account the constraints.

One of the well-known machine learning solutions is the network agnostic algorithm for selecting the neural architecture WANN [15]. The WANN algorithm uses a variational process based on a genetic method for selecting the architecture of neural networks with a common weight coefficient, which reduces the time for adapting the selected architecture of the neural network.

In [7], the WANN algorithm was first used to solve the problems of autonomous navigation of UAVs, namely, the process of compensating for the errors of the angular acceleration gyroscope of the MEMS inertial navigation system.

However, for real-time implementation of the above neural network algorithms based on the MEMS technology of small-sized microcomputers Arduino, as a rule, the process of quantizing the neural network is required [16]. The quantization algorithm is usually used to reduce the dimensionality of the architecture of a neural network, but the accuracy of such neural networks decreases by 20–30 %.

For today, for the development of intelligent navigation systems, dynamic neural networks are mainly used [17], which allow avoiding the quantization process without losing the accuracy of the neural network model. Therefore, it is proposed to consider alternative algorithms based on extreme machine learning ELM, which were presented in [18, 19].

Thus, the object of research is the process of controlling the UAV trajectory in an autonomous flight mode based on neural network algorithms. And the purpose of the work is to use neural network algorithms as a trajectory control system UAV in an autonomous flight mode, the essence of the experiment of which is the process of reducing the deviation from the target UAV trajectory under conditions of a sudden disappearance of GPS signals.

2. Research methods

In general, the UAV trajectory model is based on the data of the navigation system of the global GPS positioning system and the processes of MEMS inertial navigation system of the advanced Madgwick filter. In essence, the model of the UAV trajectory is an 18-dimensional state vector, shown in the equation:

$$P = \left[\varphi_{E,N,U}\ \Delta V_{E,N,U}\ \delta_{l,\lambda,h}\ \Delta g_{x,y,z}\ \Delta a_{x,y,z}\ \Delta m^{E}_{x,y,z}\right]^{T},$$

where $\varphi_{E,N,U}$ – vector of the orientation error relatively to the UAV platform, which is the projection of the Earth's rotation of the axis (east-north-up); $\Delta V_{E,N,U}$ – the errors of the UAV velocity data relative to thelocal UAV coordinate system; $\delta_{l,\lambda,h}$ – error is longitude, latitude and altitude; $\Delta g_{x,y,z}$ – errors in the constant deflection of the gyroscope in the coordinate system relative to the MEMS sensors; $\Delta a_{x,y,z}$ – errors of constant displacement of the accelerometer; $\Delta m^{E}_{x,y,z}$ – errors of the magnetometer (ferromagnetic effect) relative to the determination of magnetic north, index E – reference model of the magnetic field.

In the time of the sudden disappearance of the global positioning system signal, to determine the estimate of the positioning of the UAV, that is, (the speed and position of the UAV), a neural network algorithm is used to replace the GPS signal for forecasting the position of the UAV.

An experimental study of UAV trajectory control processes during the disappearance of GPS signals is presented in two experiments.

In the Matlab environment, a model of the process of disappearance of the signal of global positioning systems

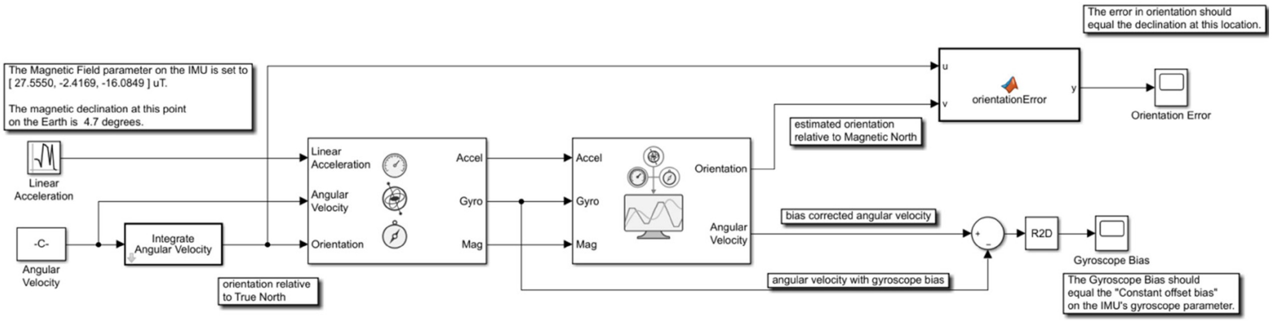

Fig. 1. Simulation model of Simulink Matlab navigation parameters processing

during 300 s of a UAV flight was built (Fig. 1).

The experiments were carried out in the Simulink Matlab software environment (version 2020.b) and the Python programming language using the open source Google Tensor Flow libraries (version 2.1.0), for deep learning using a real SINS sensor data set. The experimental platform is based on the ProsKit Bx-4123 development board (USA).

Taking into account the initial data, limitations and assumptions, the positioning of the unmanned aerial vehicle (speed and position of the UAV) is estimated using the ELM-Kalman [19] and WANN-RNN Madgwick [16] algorithms.

Input data – vector of reference parameters of UAV positioning:

$$Q=\left\{q_1\left(\varphi_{E,N,U}\right),q_2\left(\varepsilon V_{E,N,U}\right),q_3\left(\varepsilon P_{l,\lambda,h}\right)\right\}.$$

Output data – target output parameters for predicting the trajectory of the UAV in autonomous flight mode during the disappearance of the GPS signal:

$$T=\begin{Bmatrix} q_1\left(\varphi_{E,N,U}+\Delta_{t+1}\right), \\ q_2\left(V_{E,N,U}+\Delta_{t+1}\right), \\ q_3\left(P_{l,\lambda,h}+\Delta t+1\right) \end{Bmatrix}.$$

Limitation:

– deviation from the target trajectory of the UAV in autonomous flight mode [4–6]:

$$\mathrm{T}\left(\Delta_{\omega UAV}\right)\leq\left\{0.012\ldots0.18\right\}\ \frac{1}{\mathrm{s}};$$

– neural network training period:

$$t_{lerning\ rate}\leq\left\{10\ldots100\right\}\ \mathrm{s};$$

– speed of adaptive learning of the neural network:

$$t_{adaptive\ learning\ rate}\leq\left\{0.034\ldots0.05\right\}\ \mathrm{s}.$$

Target function:

$$F\left(T\left(\Delta_{\omega UAV}\right)\right)\to\min\Rightarrow\min_{\beta}\left\|H\beta-T^{`}\right\|\Rightarrow optimum(NNA).$$

Assumption: UAV flight speed is constant.

During the experiment, a MEMS MPU-9250 sensor (USA) is used to ensure the correct measurement of the gyroscope (acceleration, angular velocity). Next, the signal received at the sensor input is demodulated and passed through a 16-bit analog-to-digital converter. The Sample Rate can be programmed from 3.9 to 8000 Samples per second.

At the next stage, the process of compensating for the influence of the sensor's sensitive elements using the built-in low-pass filter and reading data to the Arduino Nano microcomputer platform takes place.

The process of calculating the orientation of a UAV in an autonomous flight mode occurs by processing acceleration data and magnetic field data.

It is known that the main sensor that affects the determination of the UAV heading angle in full autonomous flight mode without taking into account the GPS signal is the magnetometer readings, that is, heading data. For the correctness of the experiment, the effect of ferromagnetic perturbation was simulated, which, with the help of a magnet, gradually approached the magnetometer sensor. This action was repeated three times.

The first two times the magnetic influence was applied only for 2–3 s, while the third time the influence was carried out statically (until the end of the experiment), as a result, the value differed from the norm of the reference magnetic field vector (≈0.55 Gauss).

3. Research results and discussion

Experiment 1. The purpose of the experiment is to determine the influence of the number of neurons of the hidden level of the neural network on the accuracy of approximation of navigation data.

The graph (Fig. 2) compares the result of the SINS algorithms, using the popular Root Mean Square Error (RMSE) error metric to measure the difference between the model prediction values and the reference model (with reference navigation parameters obtained from GPS). In particular, an assessment of the accuracy of determining the navigation parameters of the SINS was carried out on the basis of neural network algorithms. Thus, the result of GPS signal parameters simulation modeling:

ELM-Kalman with blue line (result of 500 neurons – accuracy as a percentage of the model with a GPS reference signal (RMSE) – 93.2 %);

WANN-RNN Madgwick with green line (result of 500 neurons – RMSE – 81.3 %).

Experiment 2. The purpose of the experiment is to determine the speed of the adaptive learning process of the UAV SINS neural network algorithms.

The experiment consisted in the fact that when testing a trained neural network, test vectors that were different from those used in the training sequence were fed to its input.

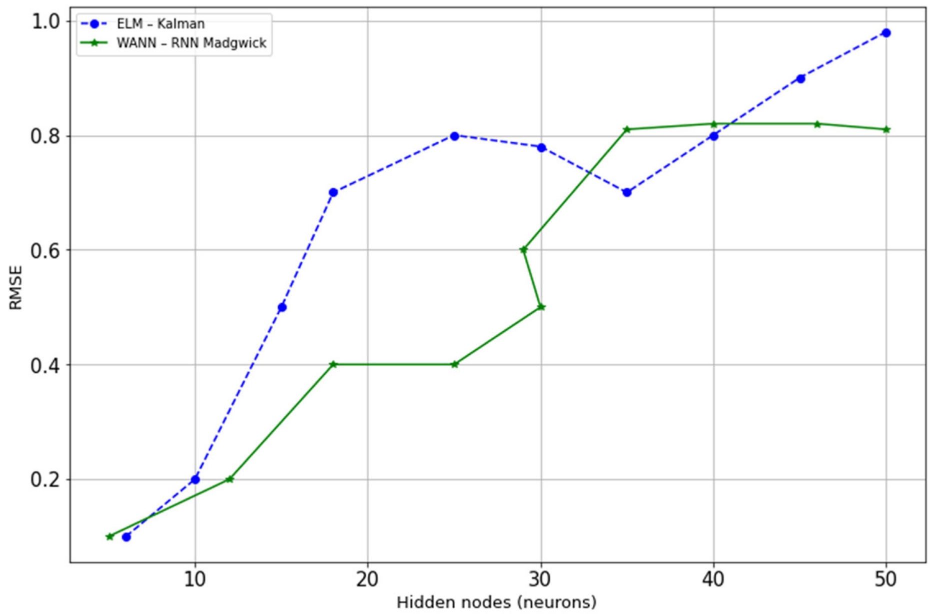

Fig. 2. Graph of estimation of accuracy of Root Mean Square Error of navigation parameters of without platform inertial navigation system on the basis of neural network algorithms with different number of neurons Hidden nodes (neurons) of the hidden level

As a result of the experiment, it was established (Fig. 3):
– SINS based on the ELM neural network – Kalman (learning rate was 0.8°/s, RMSE accuracy – 80.2 %);
– SINS based on WANN's neural network algorithm – RNN Madgwick (learning rate 0.81°/s, RMSE accuracy – 65.4 %).

The result of the experiments showed that the application of the ELM-Kalman-based algorithm provides better training accuracy for the SINS neural network and is faster than the WANN-RNN-Madgwick algorithm by 2.23 %.

However, it should be noted that the accuracy of learning improved with the number of neurons in the structure of the latent level <500, which increases the complexity of the computational load and increases the time of the learning process. This can complicate the practical implementation using micro- and small navigation UAV equipment.

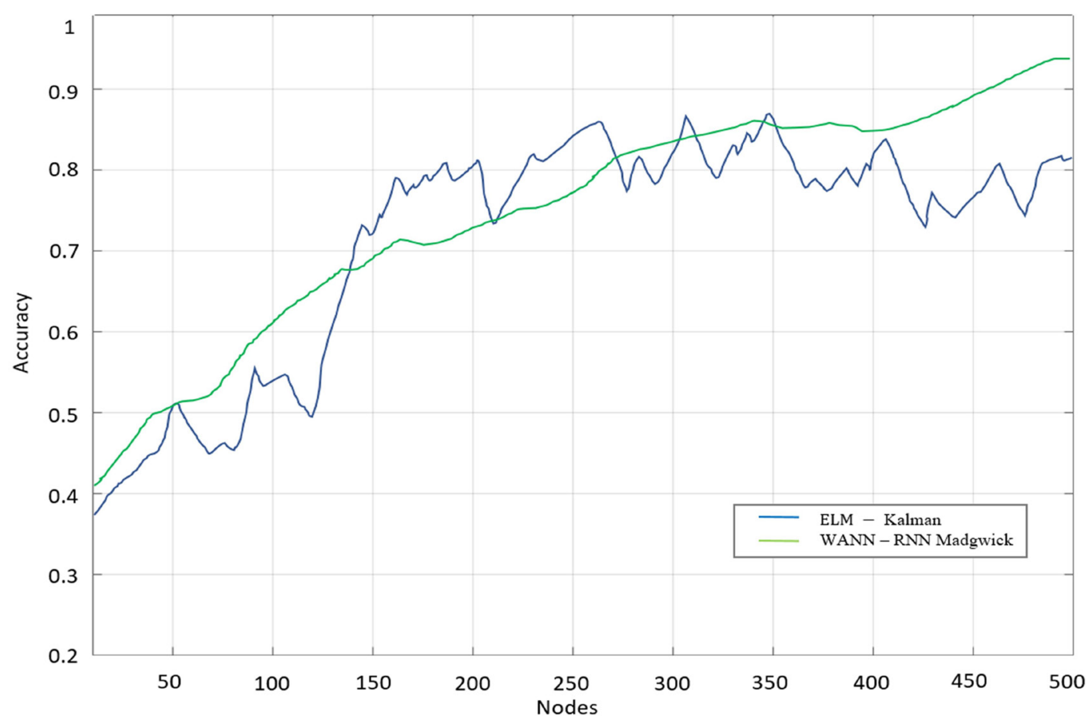

Fig. 3. Graph of accuracy (Accuracy, °/s) of adaptive learning without platform inertial navigation system depending on the number of neurons (nodes) and the type of neural network algorithm

4. Conclusions

The paper shows the use of neural network algorithms in as a systems simulating the parameters of reference signals for controlling the trajectory of UAVs in autonomous flight mode. The main task is to reduce the deviation from the target trajectory of the UAV in the event of a sudden disappearance of GPS signals.

The tendencies of development of scientific and applied solutions of application of neural network algorithms for control systems of trajectory of micro- and small UAVs as a part of platformless inertial navigation systems are analyzed. Simulation was performed in Matlab based on the initial data of the UAV trajectory model (taking into account the GPS reference parameters) to study the process of UAV trajectory control using neural networks in periods of disappearance of GPS signals. It has been experimentally established that the application of the ELM-Kalman-based algorithm provides better learning accuracy faster than the WANN-RNN-Madgwick algorithm by 2.23 %. However, learning accuracy improved with the number of neurons in the latent level structure <500, which increases the complexity of the computational load and increases the learning process time.

References

1. Santoso, F., Garratt, M. A., Anavatti, S. G. (2018). State-of-the-Art Intelligent Flight Control Systems in Unmanned Aerial Vehicles. *IEEE Transactions on Automation Science and Engineering, 15 (2),* 613–627. doi: http://doi.org/10.1109/tase.2017.2651109
2. Zhou, Y., Wan, J., Li, Z., Song, Z. (2017). GPS/INS integrated navigation with BP neural network and Kalman filter. *2017 IEEE International Conference on Robotics and Biomimetics (ROBIO).* doi: http://doi.org/10.1109/robio.2017.8324798
3. Sun, C., He, W., Ge, W., Chang, C. (2017). Adaptive neural network control of biped robots. *IEEE Transactions on Systems, Man, and Cybernetics: Systems, 47 (2),* 315–326. doi: http://doi.org/10.1109/tsmc.2016.2557223
4. Veremeenko, K. K., Krasilschikov, M. N., Sypalo, K. A. (2008). *Upravlenie i navedenie bespilotnykh manevrennykh letatelnykh apparatov na osnove sovremennykh informatsionnykh tekhnologii.* Moscow: Fizmatlit, 211–219.
5. Ding, S., Ma, G., Shi, Z. (2013). A Rough RBF Neural Network Based on Weighted Regularized Extreme Learning Machine. *Neural Processing Letters, 40 (3),* 245–260. doi: http://doi.org/10.1007/s11063-013-9326-5
6. Niu, X., Nassar, S., El-Sheimy, N. (2007). An Accurate Land-Vehicle MEMS IMU/GPS Navigation System Using 3D Auxiliary Velocity Updates. *Navigation, 54 (3),* 177–188. doi: http://doi.org/10.1002/j.2161-4296.2007.tb00403.x
7. Fesenko, O., Bieliakov, R., Radzivilov, G., Huliy, V. (2020). Experimental analysis of possibilities of application of neural networks for a management by the trajectory of flight of UAV. *Zbirnyk naukovykh prats VITI, 1,* 97–112. Available at: http://www.viti.edu.ua/files/zbk/2020/11_1_2020.pdf
8. Tikhonov, V. A. (2004). Neirosetevaia model algoritma besplatformennoi inertsialnoi navigatsionnoi sistem. *Aerokosmicheskie pribornye tekhnologii,* 47–50.
9. Fakharian, A., Gustafsson, T., Mehrfam, M. (2011). Adaptive Kalman filtering based navigation: An IMU/GPS integration approach. *2011 International Conference on Networking, Sensing and Control,* 181–185. doi: http://doi.org/10.1109/icnsc.2011.5874871
10. Jiang, C., Chen, S., Chen, Y., Zhang, B., Feng, Z., Zhou, H., Bo, Y. (2018). A MEMS IMU De-Noising Method Using Long Short Term Memory Recurrent Neural Networks (LSTM-RNN). *Sensors, 18 (10),* 3470. doi: http://doi.org/10.3390/s18103470
11. Gross, J., Gu, Y., Gururajan, S., Seanor, B., Napolitano, M. (2010). A Comparison of Extended Kalman Filter, Sigma-Point Kalman Filter, and Particle Filter in GPS/INS Sensor Fusion. *AIAA Guidance, Navigation, and Control Conference.* doi: http://doi.org/10.2514/6.2010-8332
12. Ning, Y., Wang, J., Han, H., Tan, X., Liu, T. (2018). An Optimal Radial Basis Function Neural Network Enhanced Adaptive Robust Kalman Filter for GNSS/INS Integrated Systems in Complex Urban Areas. *Sensors, 18 (9),* 3091. doi: http://doi.org/10.3390/s18093091
13. Thomas, E., Hendrik, M. J., Frank, H. (2019). Neural architecture search: A Survey. *Journal of Machine Learning Research, 20 (55),* 1–21. Available at: https://www.jmlr.org/papers/volume20/18-598/18-598.pdf
14. Gaier, A., Ha, D. (2019). *Weight agnostic neural networks.* Available at: https://arxiv.org/abs/1906.04358
15. Hubara, I., Courbariaux, M., Soudry, D., El-Yaniv, R., Bengio, Y. (2018). Quantized neural networks: training neural networks with low precision weights and activations. *Journal of Machine Learning Research, 18,* 1–30. Available at: https://jmlr.org/papers/v18/16-456.html
16. Lashley, M., Bevly, D. M., Hung, J. Y. (2009). Performance Analysis of Vector Tracking Algorithms for Weak GPS Signals in High Dynamics. *IEEE Journal of Selected Topics in Signal Processing, 3 (4),* 661–673. doi: http://doi.org/10.1109/jstsp.2009.2023341
17. Cao, Y., Jia, F., Jiang, X., Zhang, Q. (2019). Prediction of SINS/GPS Navigation Information by ELM Algorithm during GPS outages. *IOP Conference Series: Materials Science and Engineering, 612,* 032002. doi: http://doi.org/10.1088/1757-899x/612/3/032002
18. Zhao, J., Wang, Z., Park, D. S. (2012). Online sequential extreme learning machine with forgetting mechanism. *Neurocomputing, 87,* 79–89. doi: http://doi.org/10.1016/j.neucom.2012.02.003
19. Bieliakov, R. O., Radzivilov, H. D., Fesenko, O. D., Vasylchenko, V. V., Tsaturian, O. G., Shyshatskyi, A. V., Romanenko, V. P. (2019). Method of the intelligent system construction of automatic control of unmanned aircraft apparatus. *Radio Electronics, Computer Science, Control, 1,* 218–229. doi: http://doi.org/10.15588/1607-3274-2019-1-20

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