DETECTION OF ATMOSPHERIC THERMAL FLOWS BY USE OF ARTIFICIAL NEURAL NETWORK

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Abstract. This article analyses the determination of a rising thermal flow with assistance of an artificial neural network. Input data for the artificial neural network are derived from aircraft navigation equipment. The output data of the artificial neural network is the assessment of rising or descending airflow conducted in real time. Simulation is carried out in idealised conditions. The simulation revealed the dependence of absolute error on the vertical air speed component and the aircraft's aerodynamic parameters.

Keywords: rising thermal flow, simulation, artificial neural networks, aircraft flight dynamics, aircraft aerodynamics, navigation systems.

1. Introduction

Automatic control systems of aircraft have evolved in the 21st century. Thanks to this process, active UAV production and research of use in various scientific fields has started (Chiesa, Corpino *et al.* 2007).

One of the most important features of UAV flight is ultimate flight distance and ultimate flight time. In normal aircraft these features depend on the internal power supply capacity and aerodynamic characteristics of the aircraft. One of the ways to enhance the flight time or distance of autonomous aircraft is to use external energy sources.

Research concerning the use of external energy sources to provide power for aircraft flight is currently being carried out. This research has already brought practical results. Other research (Allen 2005; Langelaan 2008; Noth *et al.* 2006.; Woolsey 2005; Boslough 2002) also looks into the possibility of using external energy sources.

Autonomous machines that use external energy sources give practical results for the research of astronomical objects and oceans; these machines are extremely helpful for the environment, border security, and monitoring tasks. Rising airflow is a viable external power source that can be taken advantage of by aircraft.

Research Daniel J. Edwards investigates the use of thermals in an autonomous control system. These studies also have practical results (Edwards 2008). Under suitable weather conditions for thermal flow, the experimental autonomous aircraft flew 1.5 hours and travelled 48 kilometres without using any inner power source (Edwards 2008). Another work (Hazard 2010) investigates a method for sensing thermal flow by using Kalman's filter. Other research (Briliuk, Starovoitov 2002; Soldatova, Semenov 2006) affirms that it is appropriate to perform the identification tasks by using computer systems that can work as an artificial neural network system (ANN).

Studies concerning the use of artificial neural network system in aviation are currently being carried out. One work (Kharchenko, Alexeiev 2010) researches the use of ANN for increasing flight safety.

It is worth noting that artificial neural networks certainly act differently than biological neural networks. The structure of biological neurons has a more sophisticated mathematical model. The number of elements in the network may reach tens of billions. That is eight or nine times more than in artificial neural networks. Artificial neural networks are therefore worth consideration only as a polynomial function that is capable of providing regression and classification tasks (Kallan 2001).

We can hypothesise that the use of parallel computing systems can efficiently perform identification and prediction tasks that can help to find and to use thermal airflows in a more efficient way. For this situation, the aircraft's navigational system can obtain data from an artificial neural system in real time. In order to experimentally prove the above hypothesis, the flight of an aircraft has been simulated, using a glider's principles of flight. The simulation is used to determine whether it is possible for ANN to find thermal airflows by using the aircraft's measuring equipment to detect the thermal.

2. Methods

In order to eliminate uncertainty, the flight was simulated in idealised flight conditions: an aircraft flight simulation with established parameters and without transitional dynamics of flight processes. During this flight, the aircraft uses the flight principles of a glider and is flying at a constant speed. Complete velocity vector angle from the horizontal line matches the gliding angle (Lasauskas 2008). It was also decided that the stabiliser, trunk and keel of the aircraft do not affect resistance and take-off coefficient values. Such a decision is based on simplifying and idealising the aforementioned factors that influence flight.

The mathematical model of aircraft flight consists of several components. Aircraft aerodynamic data is needed to simulate flight dynamics. The aircraft's aerodynamic parameters are influenced by the geometry and aerodynamic profile of the wing and flight speed. On the basis of the geometry of the aircraft, flight speed, and gas/fluid dynamic parameters of the air, it is possible to calculate the aerodynamic parameters of the aircraft (Lasauskas 2008).

This data was collected with the use of the QFLR5 computer program based on XFLR5 (XFLR… 2011). The simulation was determined by these aerodynamic parameters of the aircraft: the dependence of the lift force coefficient on the coefficient of drag force, the dependence of the lift force coefficient on the wing's angle of attack, and the dependence of the quality factor on the angle of attack of the wing (Fig. 1).

This data was used to calculate the gliding angle and the complete speed vector for the specific aircraft model, which is influenced by specified air parameters (for example, vertical air flow).
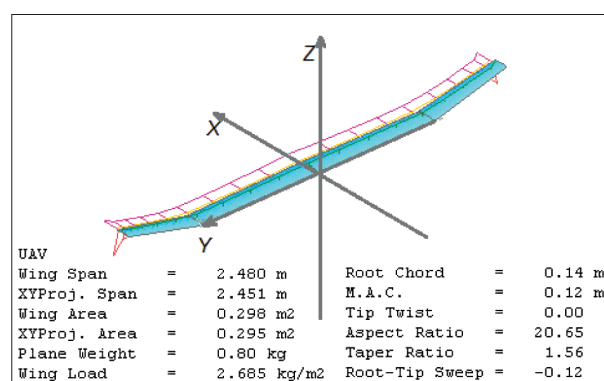

UAV				
Wing Span	=	2.480 m	Root Chord =	0.14 m
XYProj. Span	=	2.451 m	M.A.C. =	0.12 m
Wing Area	=	0.298 m2	Tip Twist =	0.00
XYProj. Area	=	0.295 m2	Aspect Ratio =	20.65
Plane Weight	=	0.80 kg	Taper Ratio =	1.56
Wing Load	=	2.685 kg/m2	Root-Tip Sweep =	-0.12

Fig. 1. Aircraft data and coordinate system

During the simulation, the value of angle of attack varied from –1 to 5 degrees. Such changes in the angle of attack were chosen because the change in angle of attack causes a change in flight speed and a change in the Reynold's number. The value of the Reynold's number was 123096 when the angle of attack was –1 degree, 56221 when the angle of attack was 1 degree, and 47113 when angle of attack was 5 degrees.

During the flight simulation at different speeds, current error will not affect the performance of the artificial neural network, because the training of ANN uses flight data with the same errors as the simulation experiment. The artificial neural network's task is to identify the value of the rising flow component from the flight trajectory function.

By changing elevator position, you can change the angle of attack of the aircraft wing. According to the polar obtained by using QFLR5, aerodynamic characteristics were determined depending on the alpha of the angle of attack.

Gliding angle is determined by this equation:

$$tg\theta = \frac{X}{Y} = \frac{1}{K} = \frac{C_D}{C_L}, \tag{1}$$

where θ is gliding angle, X is aerodynamic resistance force, Y is aerodynamic lift force, K is coefficient of performance, C_D is coefficient of resistance force, and C_L is coefficient of lift force.

When the coefficient of air viscosity is $\rho_0 = 1.225 \, kg/m^3$, full speed is determined by this equation:

$$V_{SL} = \sqrt{\frac{2 \cdot G}{\rho_0 \cdot S \cdot C_L}} = 1.278\sqrt{\frac{G}{S \cdot C_L}} = V_{HS}\sqrt{\cos\theta}. \tag{2}$$

Where G is the weight of the aircraft, S is the area of the aircraft aerodynamic planes, and V_{HS} is the horizontal component of aircraft air speed (Thomas, Miligram 1999).

The vertical component of aircraft speed, V_Y, is determined by this equation:

$$V_Y = 1.278\sqrt{\frac{G}{S \cdot C_L}} \cdot \frac{1}{K}. \tag{3}$$

Aircraft gliding angle and air speed change depending on the angle of attack. Air speed is composed of vertical and horizontal components. By adding a random value to the vertical component of the air speed, you can simulate the impact of rising and descending air flows on aircraft flight (Lasauskas 2008; Thomas, Miligram 1999).

After dynamic simulation of autonomous aircraft flight, artificial neural network initialisation is carried out, and that means it is necessary to set the random core elements to the pre-designed structure of the artificial neural network. The next step is the creation of the in-put parameters of the artificial neural network. The input data set consists of the data from the simulation of the flight dynamics: vertical air speed, horizontal air speed, aircraft angle of attack, and aircraft flight angle.

The hyperbolic tangent creates non-linear dependence between input and output data of the artificial neuron (Briliuk, Starovoitov 2002). If you replace the hyperbolic tangent with any linear function, you will get linear prediction model (Soldatova, Semenov 2006).

Every element of the artificial neural network consists of the scalar vector of the input signal multiplied by the weight factor (which is argument of activation of hyperbolic function).

$$f(a) = A\tanh(S_a), \tag{4}$$

where $f(a)$ is the value of the hyperbolic tangent's activation function and S_a is argument of hyperbolic tangent's activation function.

There are algorithms that are well suited for single-layer artificial neural network training: the 'teacher and scholar' method by F. Rosenblatt, Widrow-Hoff's training method (Briliuk, Starovoitov 2002).

In order to simulate the process, the 'teacher and scholar' algorithm was chosen, because rising air velocity and its affect on the dynamics of the flight parameters of the aircraft were known in advance. Two training data sets were provided: a set that contains training data and a set that contains result control data. Training data includes the aircraft's speed vector, angle of attack, and other calculated dynamic parameters of flight. Result control data includes the aforementioned information plus the vertical speed of the thermal flow.

To determine relative error, output data of the ANN and vertical thermal flow speed were used.

$$\delta_x = \frac{X_k}{X_t} \cdot 100 \, \%. \tag{5}$$

δ_x is relative error of measurement of the thermal flow expressed as a percentage, X_k is faulty identification of the vertical component of the vector of the thermal flow vector, and X_t is correct identification of the vertical component of the vector of the thermal flow. Relative error was found after iteration of 500 data inputs to the ANN. During every iteration the ANN resolved the full training cycle. This method was chosen in order to reduce the influence of the ANN's unsuccessful training phase on the simulation results.

3. Results of computational experiment

The artificial neural network is free from feedback and consists of several layers (Fig. 2).

The input layer does not change input data. The hidden layer is for data processing. The output layer consists of one neuron and is intended to extract output data into a vector. During simulation of aircraft aerodynamic
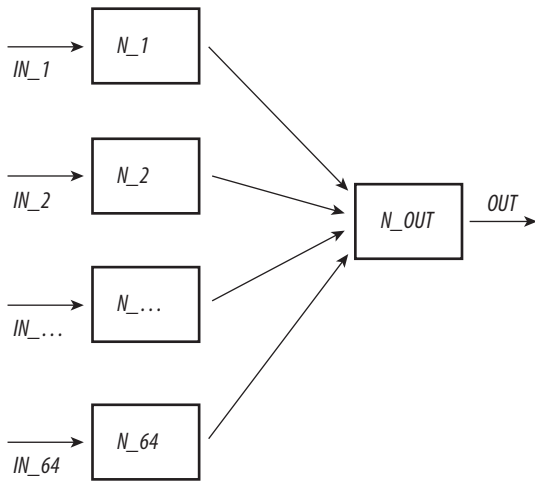
Fig. 2. Structure of the artificial neural network

parameters and flight dynamics, the data necessary to create input vectors for the ANN was received. This data has the form of flight polar (Figs 3–6).

During the test, the neural network was composed of 64 neurons in the input layer. The input layer neurons have a unit transfer function. If it is needed, the function of the activation of the input layer neurons can be changed if input data scaling is changed. There is only one output neuron. Its 64 synapses are connected to the input layer neurons. The function of the activation of the output neuron is hyperbolic tangent.

The ANN input vector is aircraft full speed, aircraft ground speed, aircraft vertical speed, angle of attack, aerodynamic quality factor, and gliding angle.

Simulation of the artificial neural network was carried out in a coherent framework for calculation. This framework is very similar to IBM's computing machine architecture. We simulated the parallel computing systems in the artificial neural network-based simulation. The program algorithm is written in C++ programming language using standard mathematical libraries.
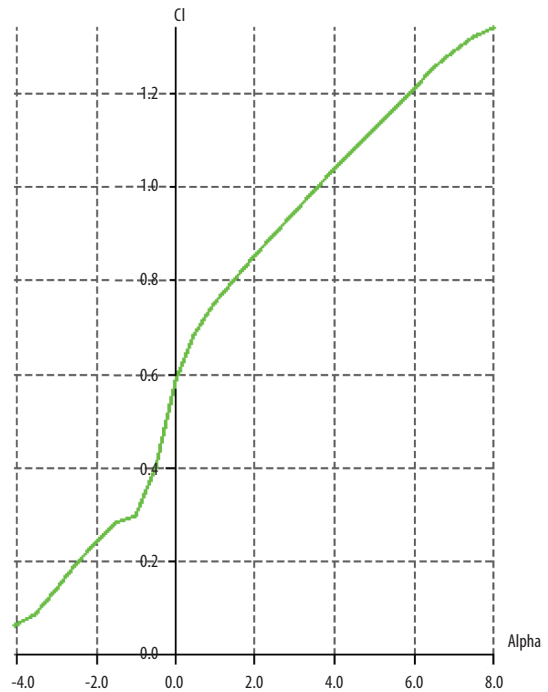

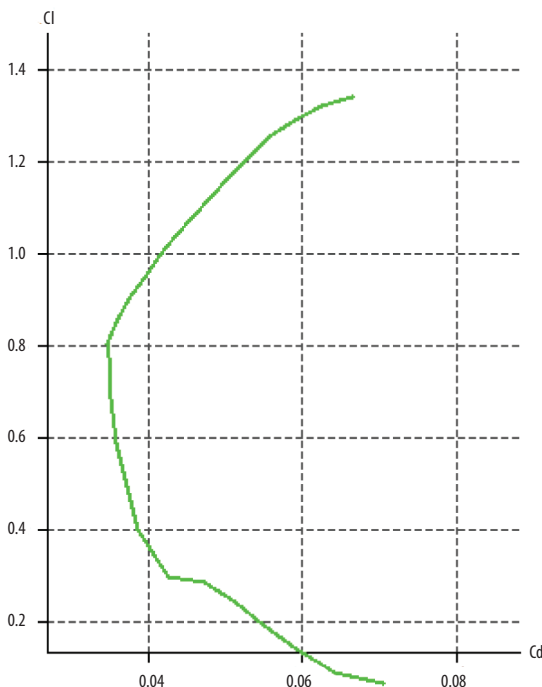**Fig. 4.** Dependence of lift force on the angle of attack

Fig. 3. Dependence of lift coefficient on the coefficient of resistance force
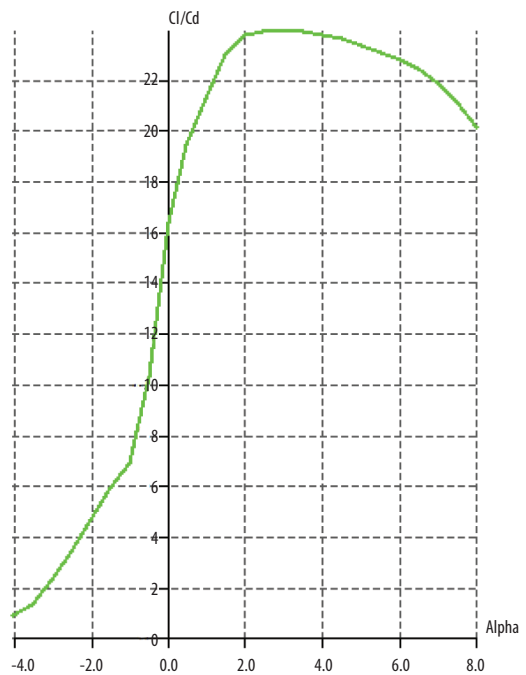

Fig. 5. Dependence of quality factor on angle of attack

The artificial neural network produces output of the time sequence from –1 to +1. The activation functions of the hyperbolic tangents of the artificial neurons cause the appearance of these values. If the output data of the ANN is positive, that means that the vertical speed of the thermal flow is positive, and if the output data of the ANN is negative, that mean that thermal flow is negative or its value is zero. The closer the value is to zero, the less likely the ANN correctly detected the presence of rising thermal flow.

The simulation showed that the artificial neural network-based identification system could successfully detect rising or descending thermal flow. The hyperbolic tangent activation function creates ANN output value that ranges between –1 to +1. It was decided that the ANN could use only integer digits (1 and –1) in order to determine thermal flows, because at these values the ANN can recognize the presence of rising thermal flow with 100% accuracy. The output values of the ANN between –1 and 1 are considered to be errors and considered to be situated in the zone of uncertainty. Sub-zero values of the vertical speed of the thermal flow create ANN output data that is in the zone of uncertainty.

The experiment showed that the size of the area of uncertainty is not fixed and varies depending on the angle of attack of the aircraft wing (Fig. 6) and the value of the vertical speed component.

The flight dynamics of the aircraft depend on the angle of attack of the wing and aerodynamic features of the aircraft. So we suggest that when the speed of the thermal flow approaches zero, the artificial neural network changes the threshold of sensitivity, below which a false identification is possible.

The simulation helped to find the margin of error of rising thermal flow in these situations: the vector of the input values of the ANN belongs to the value domain, vertically rising thermal flows have a positive speed, and vertically rising thermal flow have a negative speed, and an intersection of the aforementioned sets of data (data of positive and negative speed) exists (Figs 7–10).
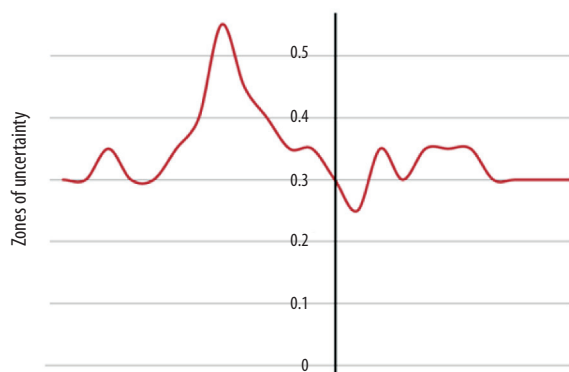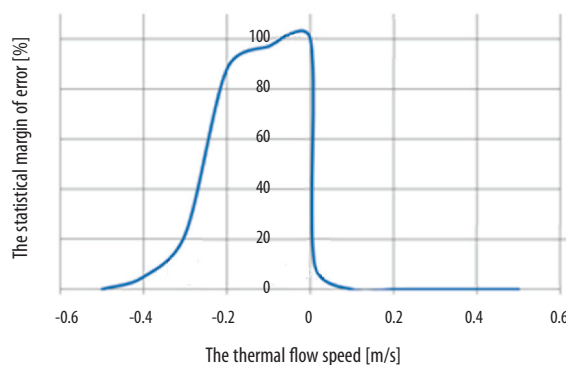

Fig. 7. Statistical margin of error detection of thermal flow when angle of attack is –0.5 degree
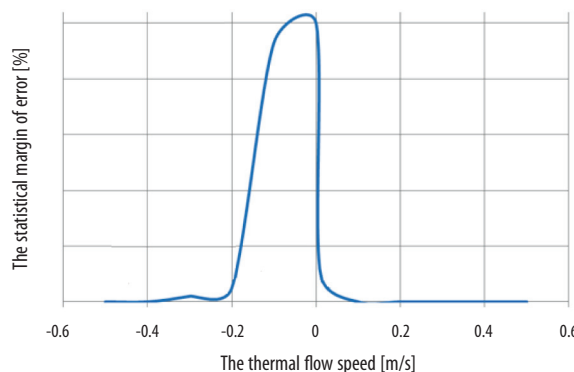

Fig. 8. Statistical margin of error detection of thermal flow when angle of attack is 0.0 degrees
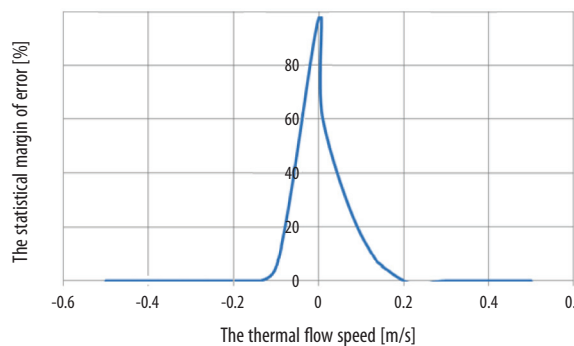

Fig. 9. Statistical margin of error detection of thermal flow, when the angle of attack is 1.0 degree

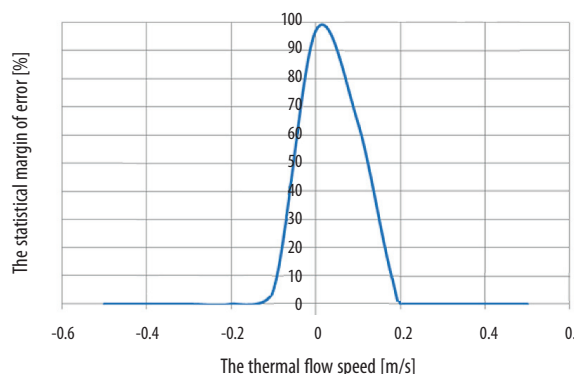**Fig. 6.** Dependence of zones of uncertainty on angle of attack

Fig. 10. Statistical margin of error detection of thermal flow when angle of attack is 2.0 degrees

In the future, it is appropriate to examine whether the use of a more complex artificial neural network is possible for not only recognition of the thermal flows but for prognosis of the appearance of a thermal flow.

4. Conclusions

During the simulation an artificial neural network model, which implements the authentication function has been realised in practice.

Artificial neural network performs functions corresponding to total energy variometer functions.

The ANN determines the speed of descending airflow outside the zone of uncertainty with 100% accuracy.

If the vertical air speed component is close to zero, the artificial neural network-based identification algorithm enters a zone of uncertainty. The value of the identification starts to fluctuate on the negative or positive side of zero.

The size of the zone of uncertainty is not fixed and varies depending on the aircraft's aerodynamic parameters and dynamic parameters.

The maximum size of determination uncertainty zone for thermal flow is 0.6 m/s.

The zone of uncertainty is not symmetric with the zero values of the vertical speed of the thermal flow and depends on the parameters of the aircraft's flight dynamics and aerodynamic parameters. The existence of this asymmetry requires further investigation

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KYLANČIO ORO SRAUTŲ NUSTATYMAS DIRBTINIAIS NEURONŲ TINKLAIS

J. Stankūnas, I. Suzdalev

Santrauka. Straipsnyje nagrinėjamas kylančio oro srauto aptikimas naudojant dirbtinių neuronų tinklus. Dirbtinių neuronų tinklų įėjimo duomenys yra gaunami iš orlaivio navigacinės įrangos. Dirbtinių neuronų tinklų išėjimo duomenys kylančio arba besileidžiančio oro srauto įvertinimas vykdomas realiuoju laiku. Modeliuojama idealizuotomis sąlygomis. Modeliuojant nustatyta santykinės paklaidos priklausomybė nuo oro srauto greičio vertikaliojo sando dydžio ir aerodinaminių orlaivio parametrų.

Reikšminiai žodžiai: kylančio oro srautas, modeliavimas, dirbtinių neuronų tinklai, orlaivio skrydžio dinamika, orlaivio aerodinamika, navigacijos sistemos.