# FLIGHT CONTROL FOR MICRO AERIAL VEHICLES USING A MODULAR NEURAL NETWORK APPROACH

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## Abstract

This paper describes the current development towards an intelligent, adaptive flight control system for micro aerial vehicles (MAV) using artificial neural networks (ANN). This work is part of the *CAROLO* programme at the Technische Universität of Braunschweig, which started in 2001 and is now focussed on the *CAROLO T200* micro plane used to carry multiple payloads like cameras or meteorological sensors. Since MAVs are high-dynamic systems which are very sensitive to atmospheric influences, controller design and optimisation are difficult tasks. As a new approach statistical methods were used to investigate if the learning aptitude of groups of neural networks is suited to use them as part of a flight control system. Here, the goal is to implement an online-adaptive flight control system provided with offline-trained basic knowledge which is improved during operation. The training phase showed that the learning task can be achieved by multi-layered feedforward-networks which replaced the standard controllers. The simulation of the implemented neuro-controllers showed robust behaviour even under difficult wind conditions just with the basic knowledge adopted during the training. The statisic analysis of groups of networks concerning reliable, not coincidental behaviour turned out to be successful. Also the specialisation of the individual networks on different parts of the control process proved to be a central aspect of the control strategy.

## 1 Introduction

The goal of the research project *CAROLO* of the Insitute of Aerospace Systems at the Technische Universität of Braunschweig was definded in 2001 as follows: A completely autonomous micro aerial vehicle with dimensions as small as possible. The *CAROLO P50* which was completed in 2004 is an aircraft with 50 cm wing span and a take-off mass of only 540 g; it takes off automatically, flies independently along predefined waypoints and is able to send payload data to the ground. After the P50 more micro planes were added to the CAROLO-family, varying in size for different missions and development purposes. An overview of all developed planes, their special hardware and the on-board navigation system can be found in [1]. The research concerning adaptive flight control strategies is focussed on the *CAROLO T200* (200 cm wing span) which is mainly used for present applications.

Micro Aerial Vehicles as a part of the Unmanned Aerial Vehicles (UAV) have become more important recently, not only for flight research purposes (e.g. navigation, flight control) but also for mission-specific applications such as environmental monitoring or meteorological measurements. Many systems have achieved a degree of automation adequate for many possible applications but still there are certain aspects which can highly improve the capabilities of these aircraft - especially concerning micro-sensors, GPS/INS-navigation and flight control. Besides the enhancement of classical control strategies one can use machine learning techniques to implement an adaptive flight control system which could augment the abilities of unmanned aircraft. There are different methods under research how to construct these intelligent control systems like fuzzy logic, neural networks or combinations of both approaches; the learning task, which is an optimisation problem can be solved with gradient descent methods or for example with evolutionary algorithms ([2], [3], [4], [5]). Since control stability of control systems based on artificial intelligence (AI) is not easily proved, a combination of classical and adaptive controllers is possible as proposed in [6]. Here, the neuro-controller is acting as an add-on to the standard control loop so that a stable basic function is improved by an ANN-controller.

When using artificial intelligence for flight control purposes it makes sense to see the aircraft as an intelligent agent [7] since it is capable of perceiving its environment, reacting accordingly and learning from experience. This idealised goal of an intelligent, absolutely autonomous aircraft is depicted in Fig. 1. The agent uses a neural controller which adapts its knowledge according to online critics.

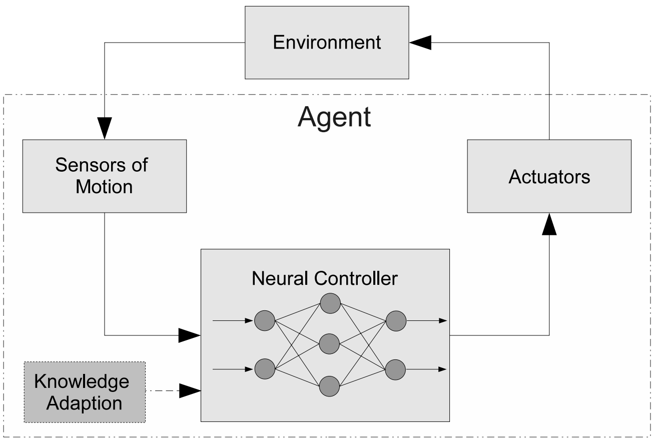


Figure 1: The ideal aircraft is acting as an intelligent agent - observing its environment and acting due to its knowledge. Over time it learns from experience

This paper analyses how far a neural network approach may contribute to such an adaptive flight control system for unmanned micro planes. Additionally, it is shown that neural flight control is generally able to avoid the time-consuming work of controller tuning and optimisation by teaching the necessary basic abilities offline. Due to the problem that permanent robust behaviour of ANNs during operation is hard to proof, a new approach is made to verify the abilities adopted during the learning phase. To do so the training data was presented to different networks varying in size while every architecture was used at least five times to ensure that training success of one network-type is not random. Subsequently, the training results of all networks are analysed statistically to understand if all or at least many networks solve the problem adequately. This especially comprises generalisation capabilities and robustness criteria, so that afterwards the offline-trained neural controllers can be validated in the simulation.

# 2 Basic System and Neural Control Approach

The neural control strategy is based on the existent control system for the *CAROLO T200* micro plane [1]. In this traditional approach lateral and horizontal movement are controlled by two cascade control loops consisting of a combination of PD and PI elements. In the first loop there is a damper to reduce high-frequency oscillation, followed by a basic controller and the autopilot in the outermost loop to control the flight path accuracy. There, a notable improvement of the system´s performance is realised by implementing the commanded trajectory on cubic B*é*zier-splines which are interlinked with each other to create the flight path of a mission. These splines are defined by four points given in the geodetic coordinate system and can be determined by

$$x(t) = a_3 \cdot t^3 + a_2 \cdot t^2 + a_1 \cdot t + x_0 \qquad (1)$$

$$y(t) = b_3 \cdot t^3 + b_2 \cdot t^2 + b_1 \cdot t + y_0 \qquad (2)$$

where t is the parameter defining the position on the spline ($0 \leq t \leq 1$) while $a_1 = 3(x_1 - x_0)$, $a_2 = 3(x_0 - 2x_1 + x_2)$ and $a_3 = -x_0 + 3x_1 - 3x_2 + x_3$. The coefficents $b_1 - b_3$ from (2) are calculated likewise simply using $y_0 - y_3$. The main advantage of this method is that the desired flight attitude can be determined beforehand for every point on the trajectory. This information is used as an additional input signal which supports the accuracy of the flight path control process; it is also used for the neural controllers to have more input data.

Previous studies have shown that a reliable neural controller with multiple outputs is hard to train, because the minimisation of the output error is always a compromise between the signals which form the output vector. Hence, a main idea was the specialisation of the neural networks on certain functions of the whole control loop. Therefore, to examine the possibility of teaching basic knowledge to a neural control unit, in every loop (lateral and horizontal) one element was replaced with a neural controller; to these the non-linear behaviour of just one output signal was tought. The generalisation abilities of these modules were expected to be reliable since ANNs are able to approximate complex functions accurately.

Besides the input signals used by the replaced controllers a time delay was added so that historical data from the sensors and from the output signal are available as network inputs [8], observable in Fig. 2. This is done because the coherence of the inputs and outputs of a high-dynamic system like a plane is time dependent - just the current inputs of a process are not sufficient to mirror the desired non-static behaviour. Therefore, a wider time frame is used as input to ensure that the time-dependent dynamic behaviour of the system is reproduced by the network. A kind of short term memory is implemented since the current output is also influenced by the provided historical data.

The neural networks applied for each controller are standard feedforward-networks using a sigmoid transfer function and a linear function in the output layer respectively often

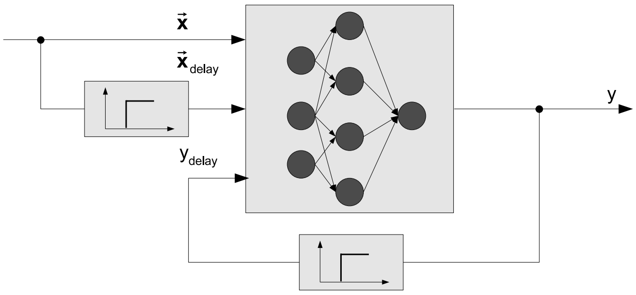


Figure 2: Principal design of each neural controller; the delayed inputs ensure the learning of the dynamic behaviour

used for control purposes [9]. Since the knowledge of ANNs is stored in the connection weights they have to be optimised during the training phase. For this application it is realised with the backpropagation-algorithm, a gradient descent method. For every training (input-) pattern the desired target value (every neuro controller has only one output) is known so that the resulting squared error of the output signal after propagating the inputs through the net can be calculated by:

$$E = \frac{1}{2}(\tau - y)^2 \tag{3}$$

where $\tau$ is the desired output and $y$ the signal propagated by the network. Now the change of the weights, the step size of one optimisation epoch, can be determined by the following general equation:

$$\Delta w_j = -\mu \frac{\partial E}{\partial w_j} = -\mu \mathbf{J} \tag{4}$$

with the learning rate $\mu > 0$ and the Jacobian matrix $\mathbf{J}$ of the error function E. There are certain aspects concerning this basic algorithm: using a constant, not variable learning rate leads to weak performance on plateaus or in local minima since the gradient is nearly zero and so is the step size. If the gradient is high on the other side, it is possible that the step size becomes so large that the global or a nearly global optimum is simply missed [9]. To improve the convergence behaviour of this algorithm it can be expanded to a Newtonian method which uses the Hessian matrix $\mathbf{H}$ in addition to the Jacobian $\mathbf{J}$ to calculate the changes in the connection weights. Using a generalised matrix-notation this expansion has the following form:

$$\Delta \mathbf{W} = -\mu \mathbf{H}^{-1} \mathbf{J} \tag{5}$$

where $\Delta \mathbf{W}$ marks the change in the weight matrix. This algorithm improves convergence in the proximity of minima but tends to be slow because of the computation of the second derivation of the error function. This can be avoided by using the following approximation for the Hessian matrix:

$$\mathbf{H} = \mathbf{J}^{-1} \mathbf{J} \tag{6}$$

This algorithm is called Levenberg-Marquardt backpropagation and was used for the training of all networks. It uses a variable learning rate and provided adequate training results.

These results discussed in the following sections are taken from the control loop for lateral movement to focus on one element. The neuro controller uses its input signals to provide the desired roll-angle $\Phi_c$ which is used to generate the neccessary aileron signals to meet the commanded trajectory.

# 3 Training Results

In the training phase the controller learns the necessary basic knowledge offline so it can be implemented into a simulation or onboard. It is clear that this knowledge can only be as profound as the information contained in the training data. Hence, to ensure that the neural networks can fulfil their task properly, appropriate data has to be used. Firstly, all data sets were obtained in a MATLAB/Simulink simulation where the complete aircraft is implemented including flight mechanics, characteristics of sensors and actuators and an atmospheric model. In order to successively investigate the abilities of the ANNs as controller, manoeuvres with different complexity were used for training. Starting with a simple flight in one direction with constant altitude and observing the very low mean squared error the difficulty was raised using training patterns with climb, dive and curve manoeuvres. Because of the promising training success, all further training and testing was done with complex, asymmetric trajectories which had a flight duration of about five minutes. These training trajectories take two things into account: the amount of training patterns is big enough for a well-grounded training and the variety of manoeuvres is sufficient for good generalisation abilities concerning unknown flight paths. An example for such a trajectory is shown in Fig. 3, the altitude change during flight is not depicted here.

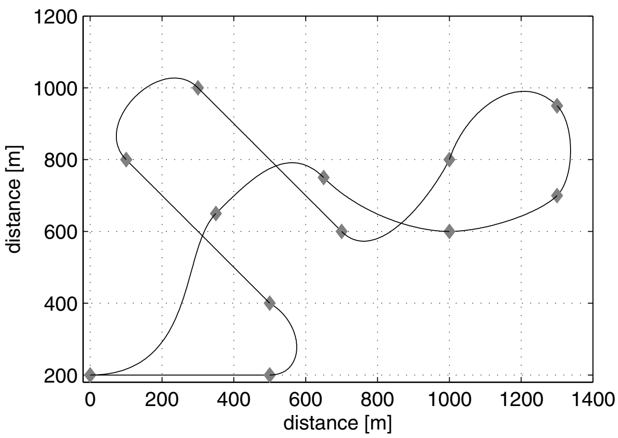


Figure 3: Example of a trajectory used to train the neural networks; start and ending point is at $x = 0$ and $y = 200$. The dots mark the intersections between splines.

To ensure a good network reaction towards unknown situations all training data was divided into training, validation and test data (70%, 15%, 15%), whereas only the training error alters the connection weights. The validation and test data is unknown to the network, whereas the training is stopped

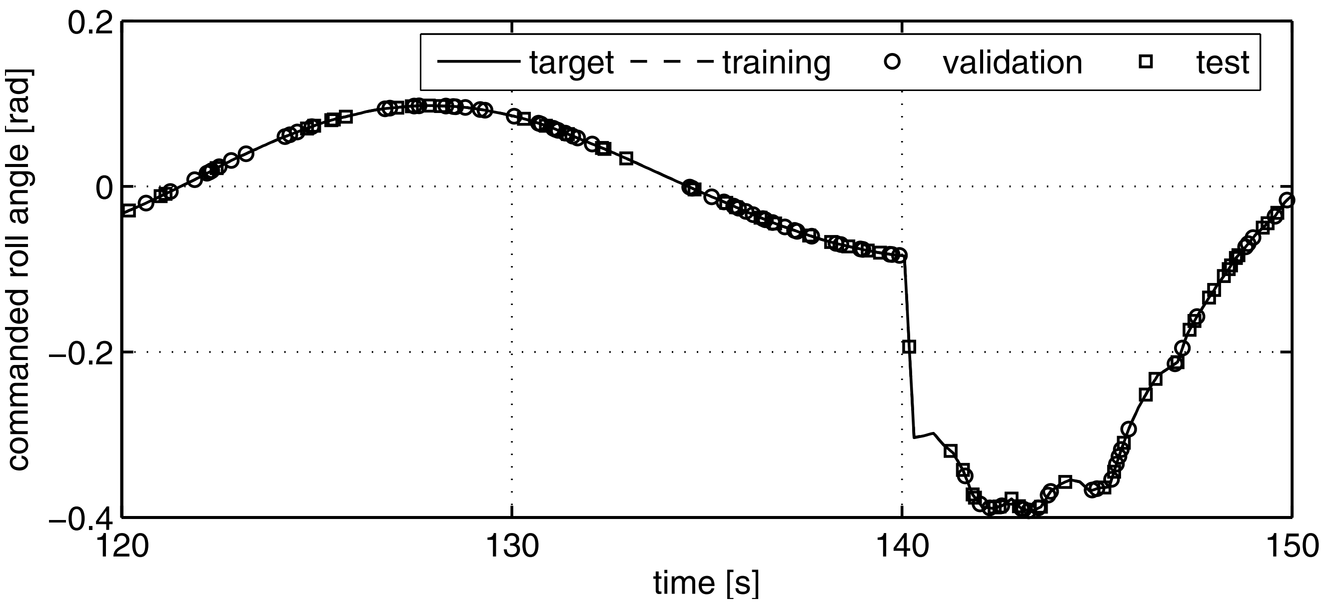


Figure 4: Network response for training, test and validation data as a section of the whole plot to ensure clarity. The output follows the targets very closely over the whole time frame of the trajectory.

when the validation error does not decrease over time. This prevents unnecessary training and also over-fitting, meaning that the training specialises on certain parts of the data without improving the generalisation abilities, which are highly important for stable performance. Hence, the mean squared error for validation and test is a first information concerning the generalisation capabilities of the neural controller. The ability of ANNs to approximate complex functions was observed when propagating the desired control signals as depicted in Fig.4.

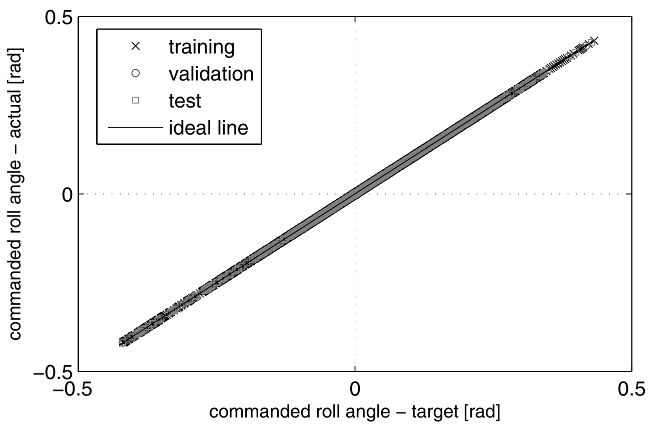


Figure 5: Network response for training, test and validation data depicted as scatter plot for all patterns used for learning. The ideal line is followed by the output which underlines the low mean squared error achieved during training.

This is an example for a three-layered network with 13 neurons in the hidden layer which is representative for all training results; the mean squared error for all networks lies at about $10^{-7}$ to $10^{-8}$ when using rather long and complex trajectories for training. In general, the neural controllers are able to reproduce the desired charcteristics with a very small error, also for test and validation, so that adequate reactions in the simulation should be expected. In Fig. 5 the results of all training patterns are depicted in a scatter plot where all outputs are plotted against the desired targets. This figure shows that the deviations are very small over the complete codomain of trained inputs, so that the close following of the ideal line also shows the training success.

After analysing the results of selected networks, an important question is if this training success is rather random or if the neural networks generally solve this problem. The examination of the mean squared error with regard to all topologies and their networks gives some information to this question and can be seen in Fig.6. There are differences in the resulting error, but generally the performance of all networks is very good. For some reason the networks with 11 neurons in the hidden layer fit best for the given control problem; for all other networks the mean squared error is nearly similar with a slight decrease when the network complexity increases. This distribution is not unusual since the correct choice of the network architecture for a given problem is rather an empiric task. Concerning this characteristic, the statistical analysis of the networks is even more beneficial because it helps to find an adequate network topology for the task.

Although all connnection weight changes are conducted offline, which means that adaption during operation is not yet possible, the trained neural control units are a good basis for test and simulation. As described in [10] the performance derived from the offline-training can be enhanced online without loosing the previously acquired knowledge. Further, the offline-acquired knowledge is necessary when thinking about flight tests with the neuro-controlled micro UAV. In the next step the ANNs can be tested as control units to verify the robustness of their behaviour.

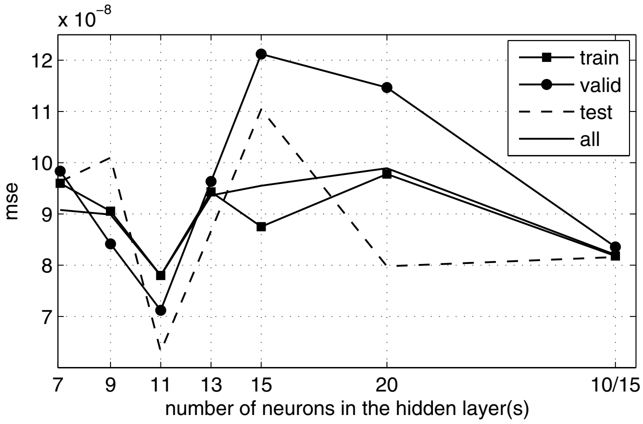


Figure 6: Mean squared error (mse) as a measure of training success for every topology used for knowledge acquirement of one complex flight trajectory. The notation $10/15$ means 10 neurons in the first and 15 neurons in the second hidden layer, giving the network two hidden layers.

Subsequently, having observed that the control process can generally be executed by feedforward-networks, the following step should be online-learning using for example the control deviation as quality criterion for the optimisation of the connection weights. Furthermore, this approach can be expanded with a neural observer, where this second ANN learns the dynamics of the system. If the dynamics are learned appropriately, one can backpropagate the resulting control deviation through the observer to generate the corresponding error of the control signal. This error signal is then used to optimise the knowledge of the controller network which leads to a more accurate training.

# 4 Simulation Results

All tests of the neural controllers were done in a simulation environment of the *CAROLO T200* micro UAV implemented in MATLAB/Simulink. All the tests were conducted including the modelling of wind and simplified turbulence to examine the generalisation capabilities observed during training considering limited atmospheric disturbences. At first every neural control unit was tested with the trajectory it was trained for to see if the specialised knowledge for one trajectory can be recalled. This is depicted in Fig. 7 for the flight path from Fig. 3 and the network discussed in section 3.

It shows the deviation for the first curve-manoeuvre beginning at about 40 seconds under the condition of wind and turbulence in relation to the training data deliverd by the analytic controller which is also not able to follow the spline accurately. Nevertheless, taking into account that the neuro-controller just works with basic knowledge the result seems adequate. The choice of the input and output signals, the use of historical measurements for the output generation and the structure of the training patterns regarding the required information for the task, seems appropriate.

Since the performance for the trained trajectories was satisfactory the neuro-controllers were tested afterwards with unknown flight paths to see if the desired generalisation capabilities and robust behaviour can be observed. In Fig. 8 a dynamic, not trained trajectory with a flight duration of about 250 seconds is represented. According to the trained trajectory with a flight duration of about 300 seconds the chosen time for the untrained track should be adequate for testing the desired generalisation characteristics.

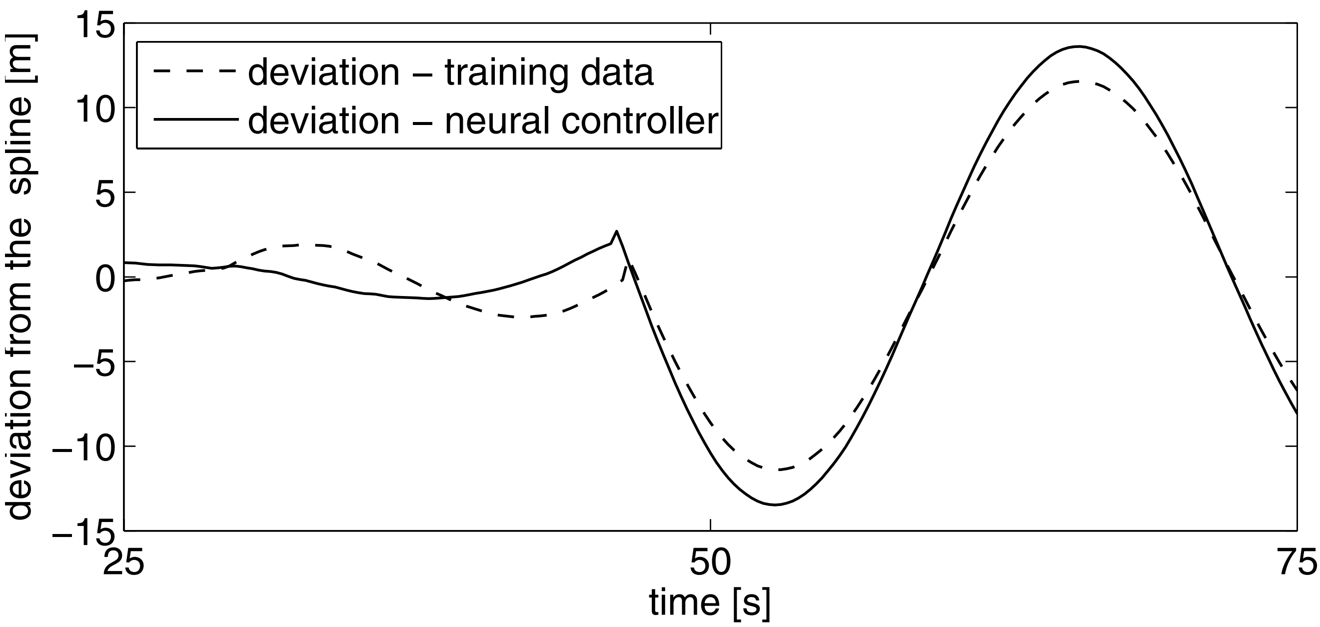


Figure 7: Deviation from the desired spline depicted as section from the complete trajectory. The ANN is capable of reacting according to the training. The resulting deviation is based on the atmospheric disturbences.

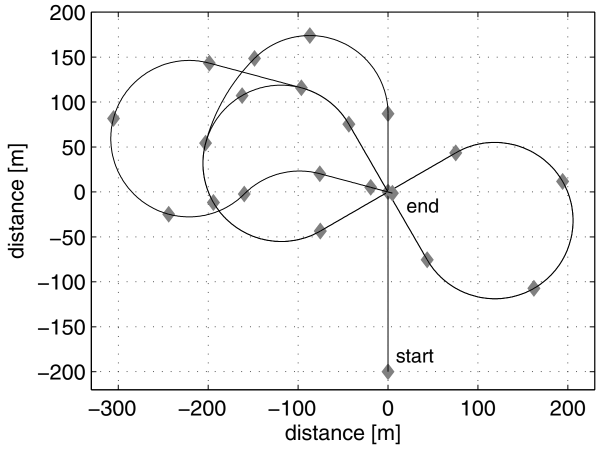


Figure 8: Example of an untrained trajectory used to test the neural controller; start and ending point are marked, after the first curve the plane enters the track formed like an eight and following it two times the UAV begins the last manoeuvre reaching the ending point. The dots mark the intersections between splines.

The aspired robust behaviour for unknown situations is the key criterion for the quality of the basic knowledge. Fig. 9 shows a section of the untrained trajectory visible in Fig. 8 using the same neural controller as before and the same atmospheric conditions. While in Fig. 7 there are slight differences, the neural controller reaches in Fig. 9 the same quality as the existent analytic controller. The deviation remains at this range for the whole trajectory. Furthermore, the track of Fig. 3 in comparision seems harder to maintain resulting from the higher control activity due to the more irregular form of the flight path, which can also be seen in the higher deviation of the the training data. Nevertheless, the neural controller is able to recall the acquired knowledge.

These results are exemplary for the good performance of the different ANN topologies, some perform better and some a bit weaker. Overall, it can be stated that the approach of using modular networks for the control purpose and analysing the topologies´ performance with statistical methods to prove their robust properties is reasonable for the layout of ANN control systems. The next step is to implement the abiliy of online-learning, so that the basic konwledge can be adapted during operation. This could significantly improve the control process for lateral and horizontal movement and offers an adaptive control strategy. Further research will deal with pure neural control but also with combinations of neural-adaptive and analytic control.

# 5 Conclusion

The application of artificial intelligence in flight control to implement adaptive critic methods giving the system a certain learning aptitude is an important approach to improve the abilities not only of UAVs. This paper shows that modular implemented neural networks are able to learn the necessary charcteristics to act as a part of a flight control system for a micro UAV. The basic layout concerning inputs and outputs, the selection of a suitable learning method and the quality of the training data are essential aspects for this control strategy. Using groups of networks and the statistical analysis of their training success provides a systematic approach to examine generalisation abilities and robustness.

The basic knowledge trained offline proved an adequate foundation for testing the neural control units and for further research especially flight tests. The two main aspects of this analysis are on the one hand the modularity of the ANN-approach granting special knowledge to every neural controller. On the other hand the statistical examination of

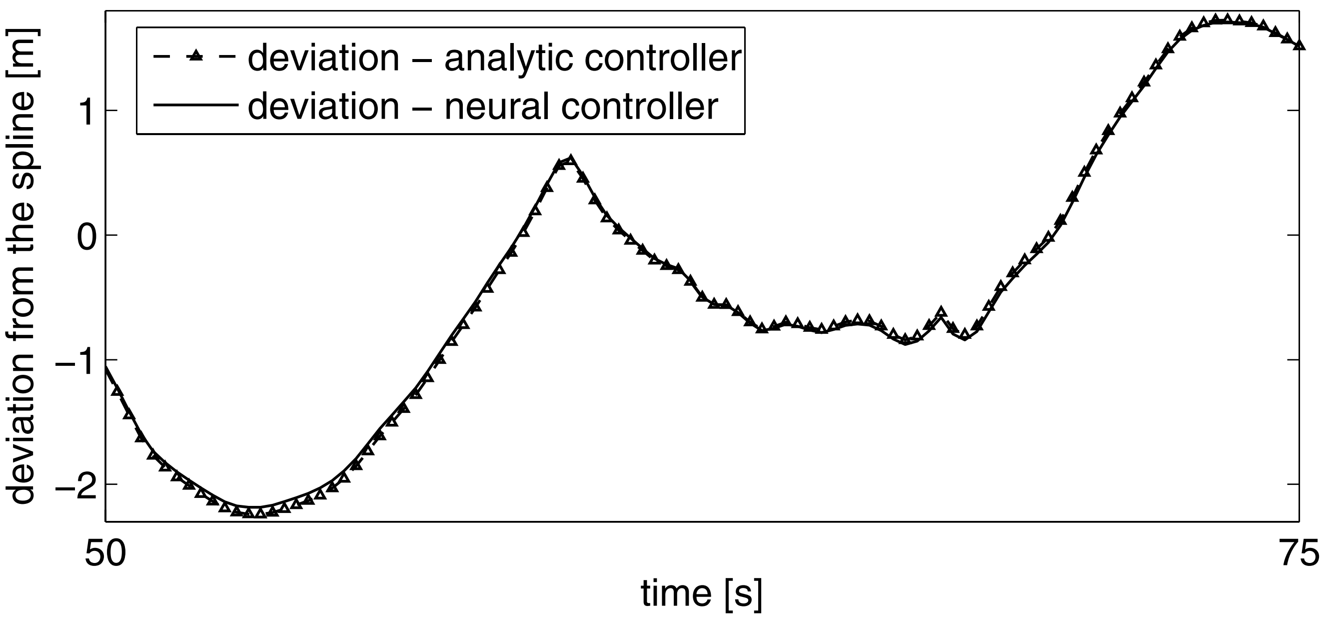


Figure 9: Deviation from the desired spline depicted as section from the complete trajectory. This trajectory was not trained, so that the generalisation capabilities of the ANN-controller become apparent.

the performance of many networks supports the whole control strategy to be reasonable and the conclusion that this approach works reliably.

Further research will concentrate on the implementation of online-learning so that the baseline knowledge of the neural controllers can be expanded during flight. For this process the main criteria for the connection weight optimisation will be the resulting control deviations. In addition, possible combinations of neural control systems with traditional strategies will be examined to consider the problem of verifying stability during the control process.

# References

[1] H-W. Schulz, M. Buschmann, L. Krüger, S. Winkler, and P. Vörsmann. The Autonomous Micro and Mini UAVs of the Carolo-Family. In *Proceedings of the AIAA Infotech@Aerospace 2005*, Arlington, USA, September 2005.

[2] R. De Nardi, J. Togelius, O. Holland, and S. Lucas. Evolution of Neural Networks for Helicopter Control: Why Modularity Matters. In *IEEE Congress of Evolutionary Computation*, Vancouver, 2006. IEEE.

[3] F.J. Gomez and R. Miikkulainen. Active Guidance for a Finless Rocket using Neuroevolution. In *Proceedings of the Genetic Evolutionary Computaion Conference*, Chicago, 2003.

[4] H. Wu, D. Sun, H. Zhu, and Z. Zhou. An Autonomous Flight Control Strategy Study for a Small-Sized Unmanned Aerial Vehicle. In *IEICE Trans. Electron., Vol. E88-C, No.10*, Chicago, October 2005.

[5] K. Bickraj, T. Pamphile, A. Yenilmez, M. Li, and I.N. Tansel. Fuzzy Logic Based Integrated Controller for Unmanned Aerial Vehicles. *Florida Conference on Recent Advances in Robotics, FCRAR, Miami*, 2006.

[6] A.A. Pashilkar, N. Sundararajan, and P. Saratchandran. A fault-tolerant neural aided controller for aircraft autolanding. *Aerospace Science and Technology*, 10:49–61, 2006.

[7] S. Russell and P. Norvig. *Künstliche Intelligenz - Ein moderner Ansatz*. Pearson Education, München, ISBN 3-8273-7089-2, 2004.

[8] U. Krogmann. *Beitrag zur Anwendung Neuronaler Netze in der Flugregelung*. PhD thesis, Faculty of Mechanical Engineering, Technical University of Braunschweig, 1995.

[9] S. Omatu, M. Khalid, and R. Yusof. *Neuro-Control and its applications - Advances in industrial control*. Springer-Verlag, Berlin, 1996.

[10] S. Ferrari and R.F Stengel. Online Adaptive Critic Flight Control. *Journal of Guidance, Control and Dynamics*, 27(5):777–786, 2004.