# Application of neuro-system for air combat process

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With the increasing capabilities of fighter aircrafts in auguring their targets with great accuracy, came the demand that fighter pilots posses higher abilities in making the correct decision, a decision based on the precise prediction of the offensive trajectory and shape of the defensive trajectory. Meanwhile, human error usually becomes a draw back to make a correct and timely suitable decision. Therefore, a control method is required to predict the offensive trajectory and execute a counter defensive trajectory . A prediction program was designed capable of predicting the defensive trajectory against an offensive one after determining three points on the offensive trajectory each separated from the other by 0.05 sec. A Neuro-system was applied to realize such counter path during the air combat process.

مع زيادة قدرة الطائرات المقاتلة فى أصابة اهدافها بدقة أصبح الطيار مطالبا بقدرات اعلى لاتخاذ القرار الذى يعتمد على التوقع السليم للمسار الهجومى وشكل المسار الدفاعى المضاد وكثيرا ما تكون أخطاء العنصر البشرى حائلا دون أتخاذ القرار السليم فى الوقت المناسب. لذلك وجب ايجاد وسيلة تحكم تستطيع تنفبذ المسار الدفاعى المطلوب بدقة بعد عملية توقع ذاتية المسار ٠ يهتم هذا البحث بعمل برنامج قادر على توقع شكل المسار الدفاعى ضد مسار هجومى بمجرد تحديد ثلاث نقاط على المسار الهجومى بفارق زمنى قدره ٠٥ و٠ ثانية حيث أن النظام المقترح قادر على أنتاج المسار الدفاعى المطلوب.

**Keywords:** Aircraft, Neuro system, Air combat, Maneuver

## 1. Introduction

When the aircraft face the attack, it must generate the counter maneuver against the offensive one of the bandit aircraft. This counter maneuver depends on the shape of the offensive maneuver.

Guez, Eilber and Kam [1] represented the important computational feature of neural network such as the associated storage and retrieval of knowledge and the uniform rate of conservations of networks for adaptive control to offer definite speed advantage. Psalties, Sideris and Yamamurea [2] studied a multi-layered neural network for a given plant. Several learning architectures are proposed for training the neural network to appropriate the input so that the desired response are obtained based on error-back propagation algorithm.

Behnam [3] represented the neural network architecture as one approach to design and implement an intelligent control system. Two simple examples are represented to study the nomenclature and characteristics of network as a control system. Peterson, Band, German, Streeter and Urnes [4] represented the use of neural network for aerodynamic parameter modeling. They represented a new construction of neural network for flight modeling and studied how to reduce the control cost and improve the flight performance.

Sadehukan and Feteih [5] represented the use of neural network controller for F8 aircraft as a dynamic inversion. An exact inverse neuro-controller with full state feedback was used and tested in presence of modeling error less than or equal to 30 %, actuators sluggishness and battle damaged or partially missing flight control surfaces.

Jargesen [6] developed a programme to demonstrate the flight using an adaptive neural network controller, capable of real time reconfiguration learning..

Born [7] developed intelligent flight control system employing experimental neural network software. The software helps pilots who find themselves in potentially disastrous situations due to severely damaged or malfunctioning aircraft. The on-line learning capabilities of the neural network software identify that something has changed and then reconfigure the flight control computer system to adapt to those effect that can effect the response of the remaining control surfaces The system is used to compensate the loss of the inoperative, damaged surfaces or equipment.

Bayoumy, Abedlghany and Ibrahim [8] used neural network and inverse dynamics concept to design forward neuro- controller for on line of control an aircraft along a predetermined trajectory. Bayoumy, Abdelghany and Ibrahim [9] used neural network approach to identify the longitudinal aircraft dynamics on line. Memory neuron is used as a model to perform on line non-parametric identification of aircraft dynamics.

In this work a prediction programme was designed capable of predicting the defensive trajectory against an offensive one. A newro system was applied to realize such counter path during the air combat process.

## 2. Manuever prediction program

Simple prediction program for the offensive of enemy path aircraft is designed. This program can generate a counter defensive path against any general offensive path. Neuro-system [10] is applied to realize such counter path during the air combat process.

The conventional control of the aircraft consists of three control surfaces, which are the ailerons that produce the rolling motion of the aircraft (banking motion around longitudinal axis). The second surface is the elevator, which produces the pitching motion (rotation around lateral axis). The third surface is the rudder, which produce yawing motion (rotation around vertical axis).

Prediction principle depends upon the generation of an imaginary path for the offensive aircraft from consequently observation of 3 real positions 0.05-second duration and generates a parabolic path through these positions. This parabola can be considered as a predicted offensive path.

The coefficients of parabolic offensive path are used to obtain the defensive trajectory, which is also a parabola with the same coefficients and opposite signs.

This will repeated continuously as follows:

1. The defensive aircraft radar observes consequently three positions of misdoubt target with discrete time equal to 0.05 second.
2. If the measured distance between the two aircrafts at a first observation d1 is smaller than the critical distance, the target is threatable.
3. If the measured distance between the two aircrafts at a second observation d2 is smaller than d1, the bandit target is closer and the threat factor is greater.
4. Measuring the angles between the velocity direction of the defensive and offensive aircraft in lateral and longitudinal planes, if these angles is smaller than the critical angle, the target is treatable.
5. Three observations are used to obtain the Predicted path of the offensive aircraft, which is assumed as a parabolic path.
6. Generate the defensive path as another parabola that decreases the threat factor.

The flow chart shown in fig 1 illustrates the above steps.

The predicted defensive path is accomplished by applying the neuro - system in [10].

## 3. Numerical case studies

*Case 1*

The positions of the offensive aircraft are: represented by three points its coordinates ($x$, $y$ , $z$) measured in feet are :
(1000, 1000, 1000), (1060, 1005, 1002) and (1160, 1000, 1000).
The corresponding positions of the defensive aircraft are:
(5000, 1000, 1000), (5050, 1025, 1002 ) and (5100, 1000, 990).
The critical threat angle is 10 degrees and critical threat distance is 6000 feet.

Table 1 shows the results obtained by the predicted program. Figs. 2,3, and 4 show the predicted air combat for the case of lateral, longitudinal and spatial motion.

*Case 2*

The coordinates of the first three observations for positions of the offensive aircraft are:
(1000, 1000, 1000), (1060, 990, 1005), (1160, 1000, 1000)
The corresponding positions of defensive aircraft are:
(5000, 1000, 1000), (5050, 1001, 1002), (5100, 1000, 999)

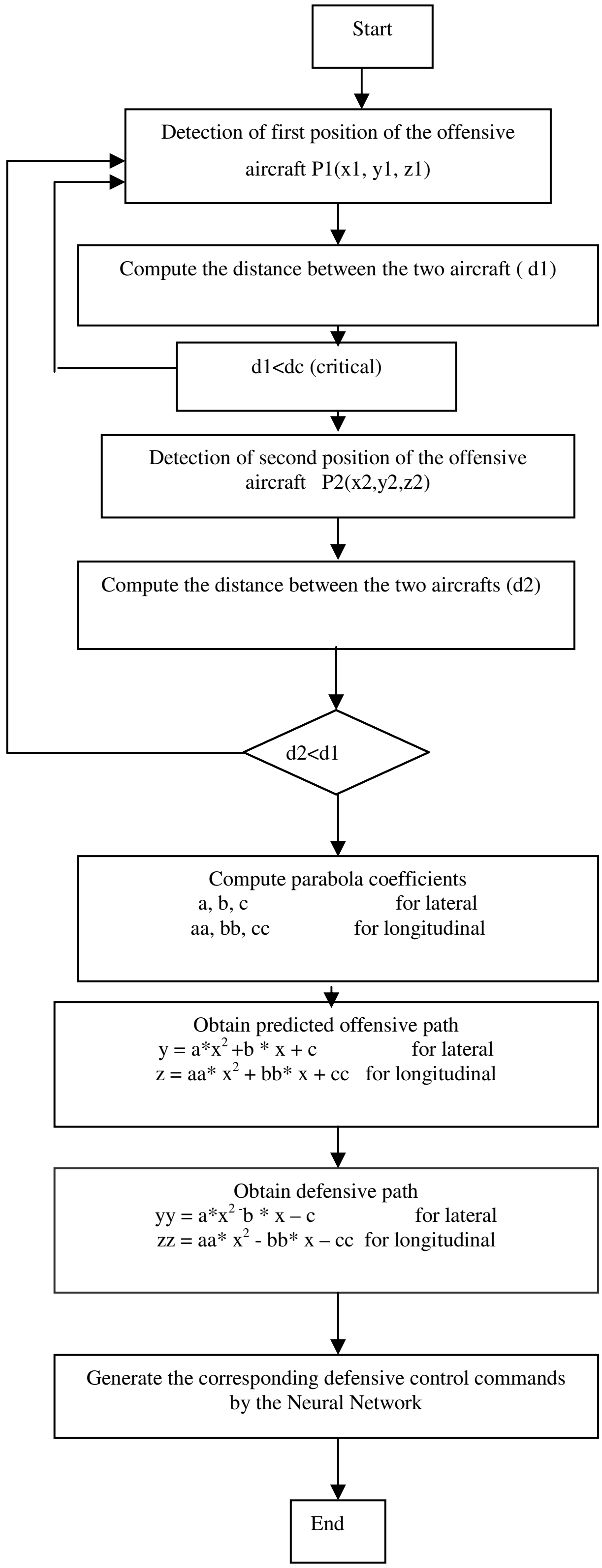


Fig. 1. Prediction flow chart.

Table 1
Output of the prediction program for case 1

| Parameter | Value |
|---|---|
| Distance at first observation | 4000 feet |
| Distance at second observation | 3970 feet |
| Lateral threat angle | 4.8 degree |
| Longitudinal threat angle | 1.57 degree |

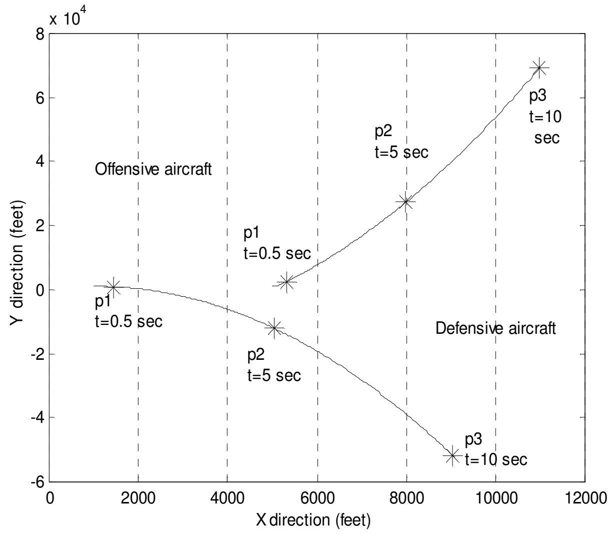


Fig. 2. Lateral predicted air combat for case 1.

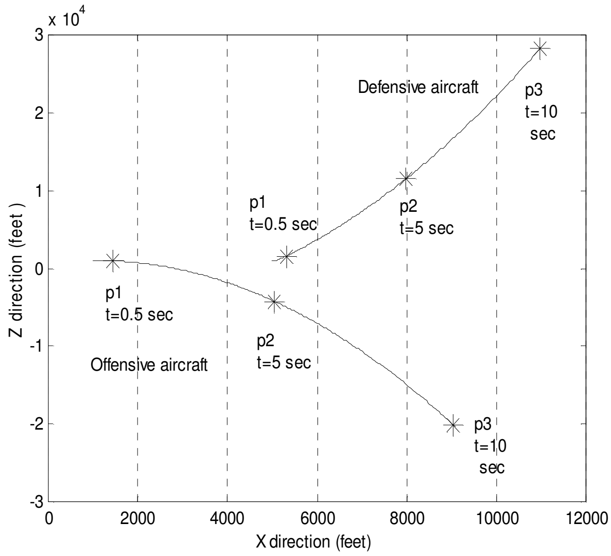


Fig. 3. Longitudinal predicted air combat for case 1.

Table 2 shows the results obtained by the predicted program. Figs. 5, 6 and 7 show the predicted air combat for the case of lateral, londidudinal and spatial motion.

## 4. Application of neuro system for spatial maneuver

Neuro system [10] is applied to obtain the required defensive trajectory. Tables 3 and 4 illustrate the comparison between control parameters of required defensive trajectory and that obtained by simulation of the designed neuro-system during a period of time of 10 second. Fig. 8 shows the predicted offensive trajectory and the required defensive trajectory, which obtained by neuro system. Fig. 9 shows the final air combat simulation for offensive, predicted defensive trajectory and the defensive trajectory, which was obtained by using neuro -systems.

The total computational time is the sum of the detection time, the prediction time, the simulation time of neuro – system along 10 sec and the selection time of a suitable neural network. The time values of the studied case on a computer Pentium 4, 128 RAM, 20, GB Hard disk are respectively 0.15, 0.35, 1 and 0.5 seconds, which gives a total time of the process of 2 seconds.

## 5. Conclusions

The suggested program is capable of predicting the defensive trajectory during air combat against an offensive one for aircraft. Neuro-systems are able to produce the required defensive trajectory.

Table 2
Output of prediction program for case 2

| Parameter | Value |
|---|---|
| Distance at first observation | 4000 feet |
| Distance at second observation | 3991 feet |
| Lateral threat angle | 9.6 degree |
| Longitudinal threat angle | 4.8 degree |

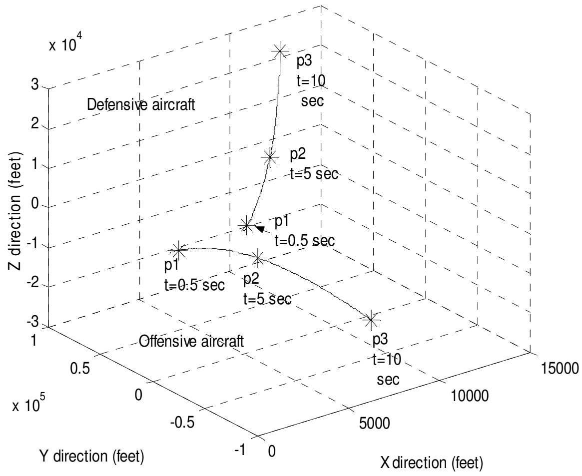


Fig. 4. Spatial predicted air combat for case 1.

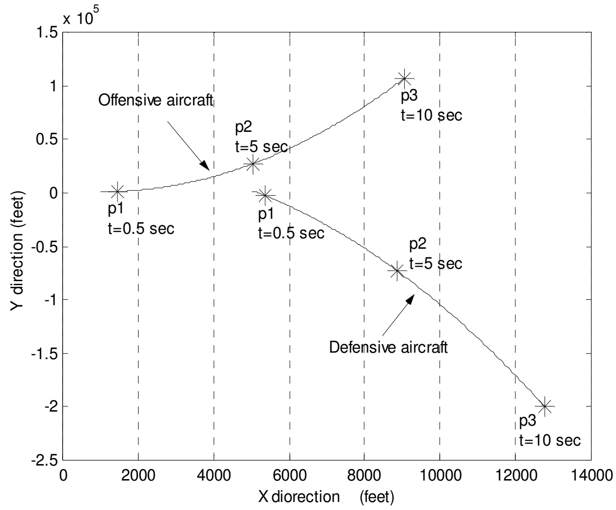


Fig. 5. Lateral predicted air combat for case 2.

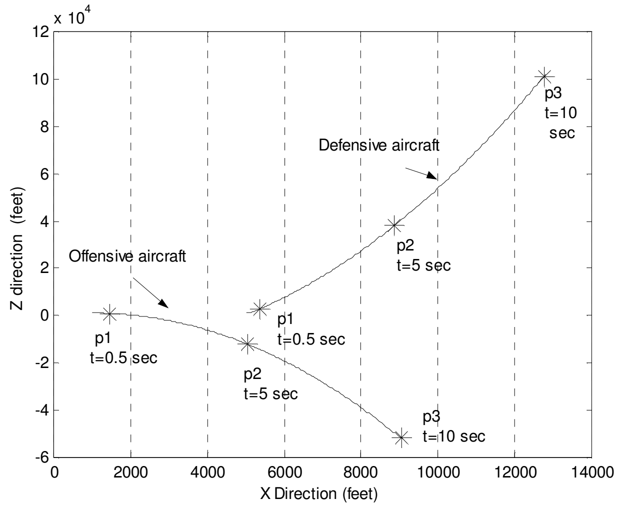


Fig. 6. Longitudinal predicted air combat for case 2.

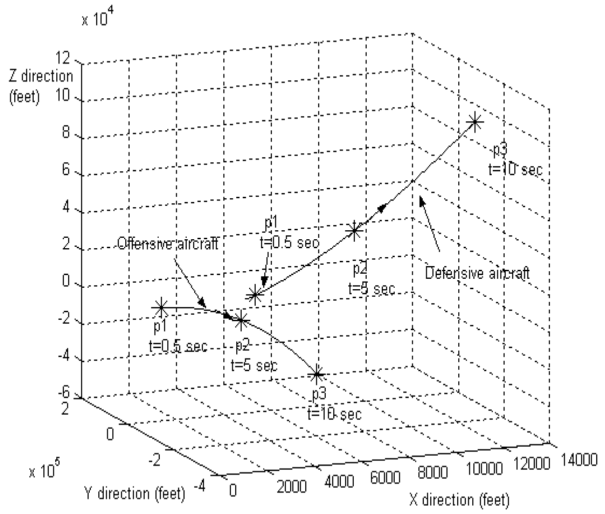


Fig. 7. Spatial predicted air combat for case 2.

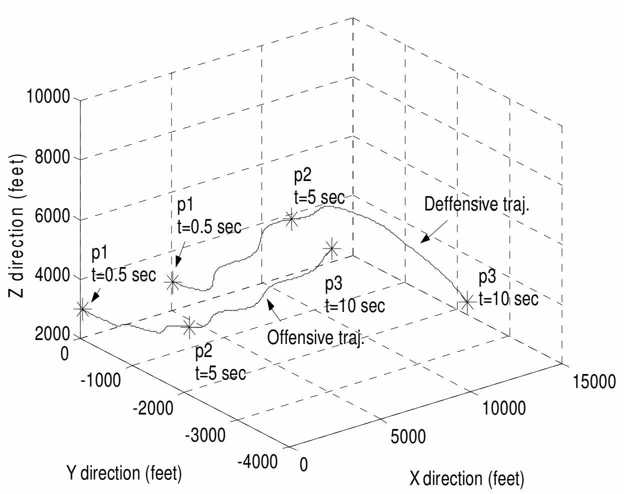


Fig. 8. Predicted offensive trajectory and required defensive trajectory.

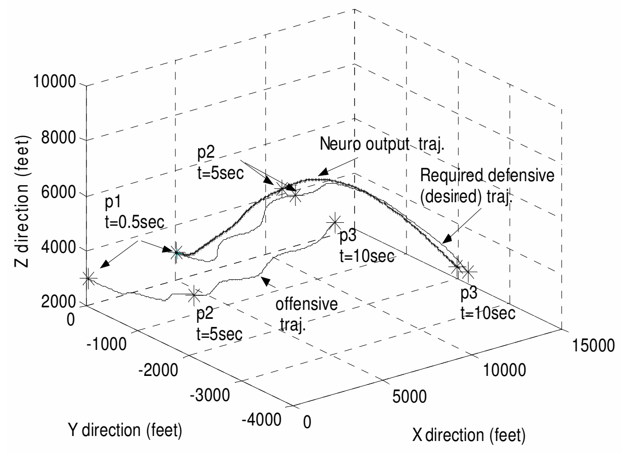


Fig. 9. Final air combat simulation.

Table 3
Real and neuro output control parameters of elevator during a period of time of 10 seconds

| Time (sec) | Real elevator (degree) | Neuro output elevor (degree) |
|---|---|---|
| 1 | 0.4573 | 0.1634 |
| 2 | 0.8277 | 0.5670 |
| 3 | 0.9954 | 0.8983 |
| 4 | 0.9194 | 1.0582 |
| 5 | 0.6183 | 0.8350 |
| 6 | 0.1658 | 0.5383 |
| 7 | -0.3273 | 0.1721 |
| 8 | -0.7402 | -0.3485 |
| 9 | -0.9720 | -0.7461 |
| 10 | -0.9657 | -0.9803 |

Table 4
Real and neuro output control parameters of bank and rudder at each second during a period of time of 10 seconds

| Time (sec) | Real | | Neuro output | |
|---|---|---|---|---|
| | Bank (degree) | Rudder (degree) | Bank (degree) | Rudder (degree) |
| 1 | 2 | 2 | 1 | 0.75 |
| 2 | 2 | 2 | 2 | 2 |
| 3 | 2 | 2 | 2 | 2 |
| 4 | 2 | 2 | 2 | 2 |
| 5 | 2 | 2 | 2 | 2 |
| 6 | 2 | 2 | 2 | 2 |
| 7 | 2 | 2 | 2 | 2 |
| 8 | 2 | 2 | 2 | 2 |
| 9 | 2 | 2 | 2 | 2 |
| 10 | 2 | 2 | 2 | 2 |

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