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RESEARCH ON ENEMY AIRCRAFT BANK ANGLE ESTIMATION FOR AUTONOMOUS AIR COMBAT

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Abstract

This paper presents research done on estimating bank angle in Autonomous Air Combat based on enemy aircraft's image. Bank angle, which is defined as the angle between the maneuvering plane and horizontal plane, implies the instantaneous orientation of enemy aircraft. Information of this angle can be applied predicting the enemy aircraft's tendency of motion. After pretreatment on images of enemy aircraft at different orientations, some available feature can be extracted and inputted into neural network. Trained network is used to be a classifier to realize another image pattern and so as to tell the corresponding bank angle. Finally through tests, results show this method is feasible.

1 Introduction

Unmanned Aerial Vehicles (UAVs) have long been considered as the future generation of aeronautical technology. UAVs design and production is now a global activity with developers or manufacturers all across the world. With multi-role systems onboard, possessing the ability to tolerate complex and adverse conditions, they have been employed for a variety of missions. Specifically in military field, incorporated with long-range detection sensors and high-precision strike weaponry systems, UAVs are well competent at monitoring, reconnaissance, decoy, even at air combat. In regard to air combat, although the UAV could perform with full autonomy have not revealed yet, the Autonomous Air Combat (AAC) technique designed for such formulation has been mentioned.

Related researches on AAC have been conducted for recent decades. NASA funded the studies of a Trial Maneuver (TM) method for dealing with dogfights between two fighter aircrafts. At each decision point in air combat, taking relative geometrics and dogfight experiences into account, a set of maneuvers or inputs can be chosen for own aircraft. After extrapolating both the own and enemy aircraft future orientations and positions, a scoring model on friendly aircraft will judge of these choices and then select the optimum one for itself to get advantage position [1]. The whole process is shown as the blocks in Figure 1. Along with the iteration, this process repeats.

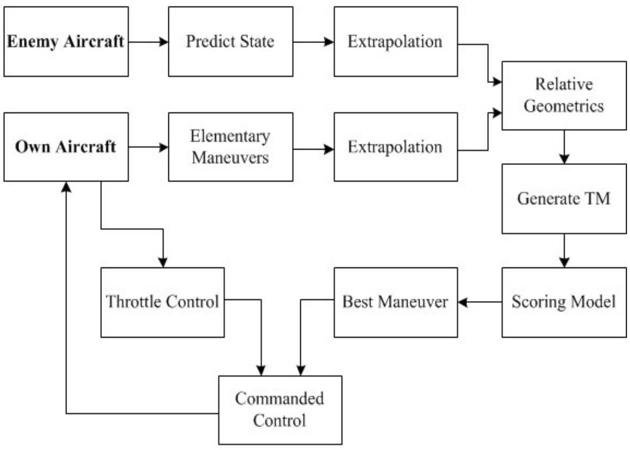

Figure 1. Trial Maneuver Method System

Accordingly, prediction of own/enemy aircraft movement is a fundamental part of the AAC technique. Upon this technique, a bank of different maneuvers/input of the aircraft are considered; based on the prediction of own and enemy aircraft movement, a most promising maneuvers/input is selected and will be executed.

The authors have conducted a research on own aircraft movement under different control surface input of the aircraft, and in this report we mainly discuss the enemy aircraft movement. Generally, a coordinated flight without sideslip is preferable to all pilots. Given maneuvering plane of the aircraft, movements of the aircraft could be extrapolated based on the past points. To avoid iterations of solving the aircraft six degree-of-freedom (6 DOF) dynamics equations, two control variables of aircraft flight dynamics are picked out for predicting the aircrafts future orientations and positions. They are bank angle and angle of attack. Angle between the maneuvering plane and horizontal plane is defined as bank angle. In this paper we attempt to estimate bank angle just from the images or photos of enemy aircraft [2].

2 Studies on Enemy Aircraft Bank Angle Estimation

2.1 Related Theory of Flight Dynamics

In flight dynamics, several coordinate systems are employed to describe the positions and orientations, of which two systems are involved - the ground axis system $O_g x_g y_g z_g$ and the body axis system $O_b x_b y_b z_b$ [2]. Their origins and axes are regarded as:

O_g	A fixed point on the ground
$O_g x_g$	A chosen orientation along the horizontal line
$O_g z_g$	Along the vertical downward
$O_g y_g$	Determined by right-hand screw rule
O_b	Located at aircraft's center of gravity
$O_b x_b$	Point forward out of the nose of aircraft
$O_b y_b$	Point out through the right wing
$O_b z_b$	Point downward as right-hand screw rule

The ground axis system is used primarily as a reference system to express gravitational effects, altitude, horizontal distance and the orientation of the aircraft, while the body axis system is used to define aircraft forces, moments and velocities. Concerning a flight without sideslip, the maneuvering plane coincides with the symmetry plane of aircraft. In this case, the bank angle is exactly equal to the angle between plane $O_b x_b z_b$ and plane $O_g x_g y_g$.

For an aircraft, the angular orientation of the body axis system with respect to the ground axis system depends on the orientation sequence. The coordinate systems conversion is based on the equation:

$$\boldsymbol{r}_b = \boldsymbol{L}_{bg}\boldsymbol{r}_g \text{ or } \boldsymbol{r}_g = \boldsymbol{L}_{bg}^{-1}\boldsymbol{r}_b \qquad (1)$$

In fact, the angular difference between the two coordinate systems is pitch angle θ , roll angle ϕ and yaw angle ψ . Considering the transition matrix $\boldsymbol{L}_{bg}$ is generated by rotating coordinate at these angles above sequentially, $\boldsymbol{L}_{bg}$ is defined in geometry as:

$$\boldsymbol{L}_{bg} = \boldsymbol{L}_y(\theta)\boldsymbol{L}_x(\phi)\boldsymbol{L}_z(\psi) \qquad (2)$$

Where

$$\boldsymbol{L}_x = \begin{bmatrix} \cos\phi & \sin\phi & 0 \\ -\sin\phi & \cos\phi & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$\boldsymbol{L}_y = \begin{bmatrix} \cos\theta & 0 & -\sin\theta \\ 0 & 1 & 0 \\ \sin\theta & 0 & \cos\theta \end{bmatrix}$$

$$\boldsymbol{L}_z = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\psi & \sin\psi \\ 0 & -\sin\psi & \cos\psi \end{bmatrix}$$

In the body axis system, the unit normal vectors of plane $O_b x_b z_b$ could be written as:

$$\boldsymbol{r}_b = [0\ 1\ 0]^T \qquad (3)$$

In the ground axis system, the unit normal vectors of plane $O_g x_g y_g$ could be written as:

$$\boldsymbol{r}_{oxy} = [0\ 0\ -1]^T \qquad (4)$$

The bank angle μ could be worked out by calculating the angle between vector $\boldsymbol{r}_{oxy}$ and vector $\boldsymbol{r}_g$:

$$\mu = \cos^{-1}\left(\frac{|\boldsymbol{r}_g \bullet \boldsymbol{r}_{oxy}|}{\|\boldsymbol{r}_g\| \bullet \|\boldsymbol{r}_{oxy}\|}\right) \qquad (5)$$

2.2 Image Processing and Feature Extraction

In our study, it's assumed that the 2D image of the enemy aircraft is available all the time, as which might be acquired by optical, infrared, or Kepler radar devices. A model of aircraft is constructed in 3D software CATIA, and a screen capture of this model is adopted to represent the 2D image. Naturally, a photo or image of enemy aircraft in air combat is usually not as clear as the screenshot of model shown in software CATIA. Specifically, the background of aircraft (such as clouds, landscape) will interfere with image recognition, as well as the image definition is discommodious for feature extraction. Fortunately these problems can be solved by existing image processing algorithm, including image filtering, image denoising, image enhancement, etc. Corresponding image operations will make the aircraft image convenient for next study.

In 3D software CATIA, built-in function named compass control panel is designed for rotating models in 3D environment. It provides functionality of setting three Euler angles to describe the model's angular position. In our work the aircraft model in a horizontal rightward state is defined as original state, while the Euler angles represent pitch angle, roll angle and yaw angle correspondingly. By rotating the 3D model and making a screenshot, we generate an image of aircraft at certain orientation [4,5]. As has been mentioned, in our work after three Euler angles are given in CATIA, bank angle could be calculated by equation (5). Both threshold and step of the Euler angles sampling are characterized in Table 1.

Table 1. Sampling of the Database

Euler Angles	Threshold	Sampling Step	Sampling Numbers
Pitch Angle θ	$[0^o,360^o]$	30^o	12
Roll Angle ϕ	$[0^o,360^o]$	15^o	24
Yaw Angle ψ	$[0^o,360^o]$	20^o	18

Note that as rolling motion of the aircraft has an essential impact on the aircraft banking, sampling step of rolling angle is relatively denser than the other two. Totally we have 5184 （12×24×18=5184） images and a set of data. These images are regard as the base of next work. An example of the enemy aircraft 2D screenshot image (which has an angular position of $\theta = 300^o$, $\phi = 60^o$, $\psi = 40^o$) is shown in next Figure 2. In this paper, the author will give a demonstration of related image processing on this image.

Figure 2. Example of Aircraft 2D Screenshot

The image inputted into mathematical software MATLAB is read and transformed to mathematic morphology as a matrix. In our work each 2D screenshot image has 613 by 663 pixels, that is, after transformation the matrix totally has 613 rows and 663 columns. In addition, each element of this matrix represents a part of the image and is evaluated an integer number between 0 and 255 indicating colorific information (number 0 stands for the color black and number 255 stands for the color white). This digitizing image operation makes it convenient for subsequent image processing. If we define that the elements of aircraft area are evaluated number 1 and the elements of background is evaluated number 0, the magnified nose part of aircraft in Figure 2 is shown as it in Figure 3. We will see that the changes of element numbers can express the edge of aircraft distinctly.

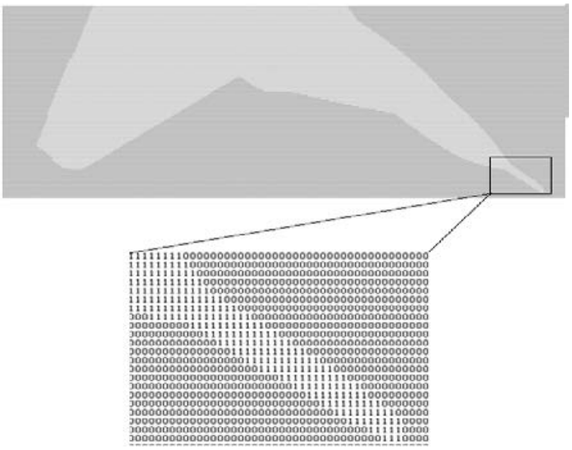

Figure 3. Part of the Binaryzation Image

Then, choose the grayscale threshold method (the threshold is chosen as 240) and change the grey level image into black and white image (BW image) just like Figure 4.

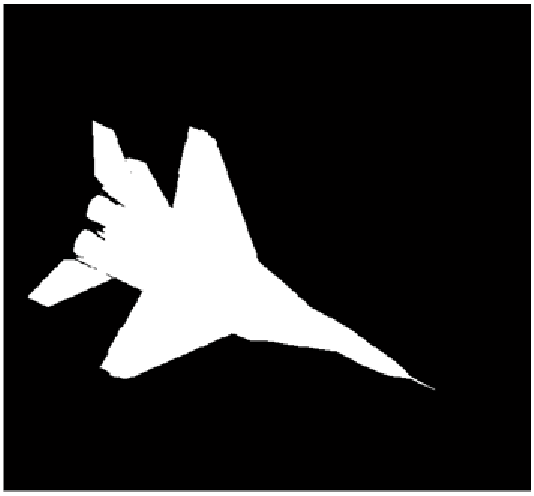

Figure 4. BW Image of the Aircraft

In some cases, hole or burr generates in BW image seen in the circles of Figure 5. By image filling algorithms, image could become smooth as it in Figure 6. Furthermore, edge detection and edge extraction algorithms help to pick out the edge of aircraft in Figure 7.

Figure 5. Hole and Burr in the Image

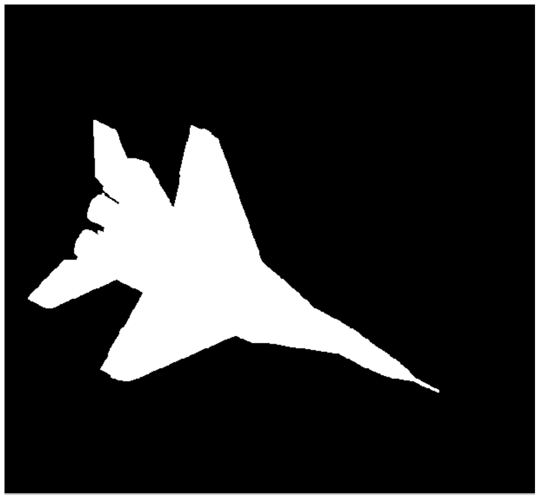

Figure 6. Image after Image Processing by Edge Detection and Edge Extraction Algorithms

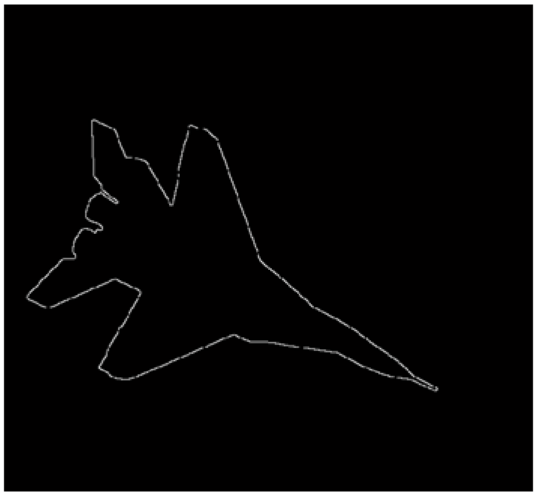

Figure 7. The Edge of the Aircraft

2.3 training Neural Network

Artificial neural networks (ANNs) are computational models inspired by an animal's central nervous systems. In an ANN, simple artificial nodes are connected together to form a network which mimics a biological neural network or the brain. Like human, ANN could perceive data and learn the information, and then work with its capacity of analysis. ANN is used in our research for image recognition [6, 7].

Probabilistic Neural Network (PNN), a kind of ANN, is used in this paper. Training algorithm of PNN is based on Bayes decision rule and is uses Gaussian Parzen windows for estimating the probability density functions (pdf) required in Bayes rule. Though several types of neural networks are adopted for classification applications, PNN is usually preferred because of its fast training speed and convergence algorithm. Prior to the network estimation, a database corresponding to different bank angles has been generated.

As defined above, bank angle of aircraft ranges from 0-180 degree. In this paper 6 levels are used to describe the classification of the angles, as shown in Table 2. In our research the estimated bank angle will be delivered to the system to extrapolated future movement of the enemy aircraft. Certainly, in such approach an estimation error could be induced; but through our simulation work this model provides a balance between computational requirements and extrapolation error bounds. Training and test of the bank angle PNN estimation net will be discussed as following.

Table 2. Classification Levels of Bank Angle

Bank Angle Threshold	Classification Level	Middle Value
$[0^{\circ},15^{\circ})$ & $[165^{\circ},180^{\circ})$	1	0°
$[15^{\circ},45^{\circ})$	2	30°
$[45^{\circ},75^{\circ})$	3	60°
$[75^{\circ},105^{\circ})$	4	90°
$[105^{\circ},135^{\circ})$	5	120°
$[135^{\circ},165^{\circ})$	6	150°

In training stage of the net input layer of the PNN structure are extracted from the 2D model. In our work, features of the image are selected from some mathematical physics meanings and mathematical characters. After several repeated attempts subsequently, we have found that different options of features have a great deal of influence over image recognition and estimation. At last we choose five features of image: height, width, area, perimeter and saturability (which is defined as the proportion of aircraft area to the whole image area), of course these feathers are uniformized before put into PNN.

For each image, as the Euler angles are known, bank angles will be calculated, and the classified level based on Table 2 is delivered to the PNN output layer. During training stage of PNN, only one value of spread which defined as sharpness of the net decision surface needs to be selected. In test stage, PNN adopts input extracted from the 2D model, and the error of estimation is defined as 1 or more levels bias between the estimated and real bank angle level. Random selection of 2000 images and other 512 images compose training sample and checking sample. The distribution of training sample is shown in Table 3, while each classification level has a similar number of samples. We distribute samples averagely in order to help PNN to learn the entire range of samples.

Table 3. Distribution of Training Sample

Classification Level	Numbers	Percentage in All (%)
1	336	16.80
2	332	16.60
3	345	17.25
4	330	16.50
5	329	16.45
6	328	16.40
Total	2000	100.00

As mentioned in the front, values of spread determine the quality of PNN's performance, what is to say, the choice of the value makes great difference in the network. Based on the theory of PNN, it's unpredictable to make sure the range of spread value before training PNN. Therefore, trial-and-error methodology is used for further research. Through the methodology, s set of curves is sketched in Figure 8 to show the accuracy rate of the estimation versus the spread value. The value of spread ranges over several orders of magnitude, as is from 10^0 to 10^7. The authors decide that spread = 0.0017 is yields a balance between the network complicatedness and estimation error. And the maximum accuracy rate of the estimation net is 66.39% accordingly, which from the engineering-application aspect if believed to be usable. With the trained PNN, we could estimate the bank angle from a processed image of enemy aircraft by inputting its image features.

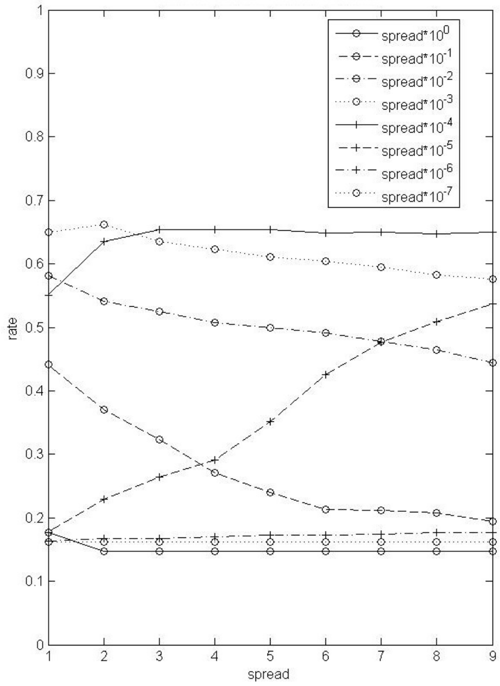

Figure 8. Accuracy versus Values of Spread

3 Conclusions and Further Plan

This paper introduces a framework for estimating bank angle of enemy aircraft. This work is developed for part of the AAC technique which is formulated to help UAVs gain a competitive advantage position in combat. Also the extrapolation work based on this estimation net has been conducted by authors, and the enemy movement prediction is accurate compared with the approaches mentioned before, particularly for rapid agile maneuvers. The prediction framework proposed in this paper is considered to with promising applicableness.

Additionally, the authors have made attempt to increase the accuracy to get better networks. Generally tentative work is bifurcated. Firstly, other networks are set up with the same training sample and checking sample, including Back Propagation (BP) Neural Network, Generalized Regression Neural Network (GRNN), Learning Vector Quantization (LVQ) Neural Network, etc. Overall, PNN is superior to the others. Secondly, other image features are extracted and considered as input of network, especially Hu-moment are tried at beginning of our research. However, the Hu-moment is invariant to scale, parallel move and rotation, and herein rotation invariance can lead to mistakes when estimating bank angles. Next, to estimate bank angle of enemy aircraft precisely, more in-depth analysis and relative research will be continued.

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