Flight Path Planning Surrogate Model Based on Stacking Ensemble Learning

To cite this article: X Z Yang et al 2020 IOP Conf. Ser.: Mater. Sci. Eng. 751 012038

View the article online for updates and enhancements.
Flight Path Planning Surrogate Model Based on Stacking Ensemble Learning

X Z Yang*, Z X Cui and X Y Qiu
Science and Technology on Avionics Integration Laboratory, 432 Guiping Road, Shanghai, 200233, China

*Email: yang_xizhong@outlook.com

Abstract. This paper proposes a method of establishing flight path planning surrogate model based on stacking ensemble learning, which can solve the real-time problem of complex flight mission’s on-line waypoints calculation. Airborne navigation system mainly utilizes several discrete waypoints to guide flight path or flight control. These waypoints are usually calculated by a set of equations based on flight dynamics, flight kinematics and flight mission constraints, and therefore path planning for complex missions cannot guarantee real-time performance. In this paper, flight samples are generated offline by taking flight mission characteristic parameters as input and flight waypoint coordinate series as output. Then two-layer coupling model is constructed based on stacking ensemble learning. A series of base-learners are constructed to learn the quantity of waypoints or each waypoint’s coordinate values respectively. At last, flight path planning surrogate model is built by combining all the base-learners, establishing the direct mapping relationship between input and output. The results show that this surrogate model can effectively calculate the aircraft flight waypoints, and meanwhile maintains ideal accuracy and real-time performance.

1. Introduction
Flight path planning is one of the main tasks of a pilot or an airborne computer in aircraft flight activities. In order to complete a specific flight mission, the corresponding flight path should be designed reasonably in advance. Aiming at different flight missions, complex mathematical analytic model of flight path planning is established via a series of simulation, optimization and iteration algorithm, and then generate a set of flight waypoints. Subsequently, the airborne navigation system conducts flight guidance and control based on these waypoints, helping to accomplish the corresponding mission process.

Path planning analytical model is generally established by the geometric optimal search theory. Meanwhile, the aircraft dynamics model, flight kinematics, mission constraints and environmental conditions are also considered. The planning space is expressed as an appropriate searching form, and then the optimal solution could be achieved via optimization algorithm or heuristic algorithm. The optimization algorithm can convert the path planning problems into mathematical programming models, and constraints such as planning time or planning area will significantly affect computational cost. The heuristic algorithm, such as genetic algorithm, particle swarm algorithm and ant colony algorithm, can simulate biological swarm intelligence, and the performance of path planning calculation still depends on the size of the problem domain. Besides, other methods such as artificial potential field method, A* method and neural network method are also in common use [1].
Path planning includes offline planning and online planning. Most of the above methods can support both offline planning and the real-time requirements of online planning when dealing with path planning problems of relatively simple flight missions. However, when the mission process gets relatively complex, the problem domain will expand rapidly, increasing the computational cost and time, even without ideal solution. For instance, in a certain flight path planning issue, it only takes several seconds to calculate 3 to 5 flight waypoints, but it will take at least ten minutes or even several hours to calculate more than 10 flight waypoints.

Aiming at solving the problem, this paper proposes a method based on artificial intelligence algorithm, which combines machine learning from flight sample data offline and invoking the training model on-line. In this way, path planning knowledge is extracted from previous offline samples to establish new online planning model, which would be used to replace the analytical model and calculate flight waypoints in real-time environment.

2. Analysis of flight path planning

2.1. Problem statement

In the research of this paper, there is a following kind of flight path planning problem. The flight mission’s information which affects the flight path can be simplified and extracted as four parameters $c_1, c_2, c_3$ and $c_4$. Specifically, $c_1, c_2$ and $c_4$ are positive rational values, $c_3$ is a positive integer. The result of path planning is a set of waypoints’ coordinate values, including longitude and latitude in earth coordinate system. The variables are defined as follows:

- $\mathbf{x}$ - input parameter vector of flight path planning model, $\mathbf{x}=[c_1, c_2, c_3, c_4]$
- $\mathbf{y}$ - output parameter vector of flight path planning model, which represents a set of waypoint coordinate values, $\mathbf{y} = \Psi(\mathbf{x})=[a_1, b_1, a_2, b_2, L a_k, b_k]$
- $k$ - quantity of waypoint, counted from $\mathbf{y}$
- $a_i, b_i$ - longitude and latitude values of each waypoint, $i=1,2,3, L ,k$
- $\Psi(\mathbf{g})$ - mathematical analytic function of flight path planning, including simulation modelling, mathematical formula and optimization iteration etc.

Since the function $\Psi(\mathbf{g})$ could be particularly complicated, its computing process will get so slow that path planning computation will not meet real-time requirement. One solution is to build a surrogate model $\Phi(\mathbf{g})$ to replace $\Psi(\mathbf{g})$ and improve the calculation speed while maintaining satisfactory accuracy.

2.2 Surrogate model

The surrogate model is a statistical model similar to a black box, whose calculation results are very close to the original model, in order to obtain some better performance (for example, the calculation time is greatly reduced, the calculation costs less resources, etc.). The surrogate model can be designed by a data-driven, bottom-up approach. First, various samples’ inputs are sent into the original model for calculating the outputs to set up a sample database. Then, a black-box model implying end-to-end mapping is generated by learning the samples of input-output relationship [2, 3].

Artificial neural network is applicable for learning the relationship between a kind of input-output mapping of mathematic model, algorithm or function, as well as constructing a classifying learner or a regression learner. However, there are several obstacles when using this method directly to learn the mapping relationship between flight mission input parameters and waypoint coordinate values. The main problem is that the quantity of waypoints in different flight missions is also quite different. Inconsistence of output numbers leads to the difficulty in determining the number of neural network’s nodes in each layer.

In this research, the flight mission sample’s input is a 4-dimension vector and the output is a 2k-dimension vector. Because the values of $k$ are variable in different samples, it’s impossible to train all
the samples in one learner. In addition, the large sample size also restricts the generalization capacity at non-sample points.

A method of ensemble learning is introduced here to solve this problem: Taking \( k \) as an intermediate eigenvalue of each sample so that all the samples are classified accordingly into different group. Samples of each group are trained separately to generate a waypoint coordinate learner at last, which containing several base-learners. When calculating waypoint coordinate, the correct base-learner is invoked on the eigenvalue of \( k \). And \( k \) can also be calculated by a waypoint quantity learner in advance from the input data by a primary learner. The method is shown in Figure 1.

\[
\begin{align*}
\text{Primary Learner} & \quad \text{Waypoint Quantity} \\
\text{Waypoint Coordinate Learner} & \quad \text{Input} \quad x \quad k \quad \text{Output} \quad y \\
C_1 & \quad C_2 & \quad C_3 & \quad C_4
\end{align*}
\]

**Figure 1.** Waypoint calculating model by ensemble learning.

### 3. Stacking ensemble learning model and algorithm

Ensemble learning is a typical algorithm of machine learning, which generates multiple learners through certain rules and trains them separately, and integrates each learner with appropriate strategies, so as to obtain better performance than a single learner [4, 5, 6]. The theoretical basis of ensemble learning is probably approximately correct (PAC) theory, strong learnable and weak learnable theories. Its representative methods include Bayes optimal classifier, bagging, boosting, stacking, random forest, etc. Among them, stacking method is a technique that integrates multiple base-learners to form an integrated learner.

Stacking method classifies the sample sets through certain rules and constructs different base-learners by machine learning algorithm. Each base-learner can be trained by different algorithm types or structures. Therefore, it’s compatible with the differences in structure, superparameters and training strategies while using stacking ensemble learning method for samples intelligent learning [7]. Stacking method can support heterogeneous integration, which is suitable for solving the flight path planning problem of learning inconsistent dimension waypoint samples [8]. After test and evaluation, if the ensemble learner fulfills the proper credibility level, it can be used for predicting output values from new input data.

For a set of sample data containing \( L \) groups data, each group is expressed as \( P = \{x_i , y_i\}_{i=1}^{M} \), where \( P \) represents the sample data set, \( x_i \) represents the input data and \( y_i \) represents the output data. \( P \) is divided into training sample data \( D = \{x_i , y_i\}_{i=1}^{M} \) and testing sample data \( T = \{x_i , y_i\}_{i=1}^{N} \), where \( L = M + N \). The stacking ensemble learning algorithm is deduced as the following process.

(1) All the samples in \( D \) are classified according to a certain strategy. Assuming that the samples are divided into \( q \) cases, the sample data set of each case is:

\[
\begin{align*}
D_j = \{x_{j,i}, y_{j,i}\}_{i=1}^{M_j} , & \quad j = 1, 2, L \quad q \\
\end{align*}
\]

where \( D_j \) represents case \( j \), \( M_j \) represents the quantity of samples in case \( j \), and \( D = \sum_{j=1}^{q} D_j \).

(2) Construct a primary learner through pre-labelled data or by unsupervised learning methods, which is used for mining eigenvalue \( z_i (i=1,2, L \quad p) \) from \( D \). The primary learner can be a single base-learner \( \psi \) or a group of base-learners \( \Psi = (\psi_i)_{i=1}^{p} \), where \( z_i = \psi_i(x_{j,i}) \).
(3) According to \( z \), new sample data set \( \mathcal{D}_\psi = \{x'_i, y_i\}_{i=1}^n \) is generated. A secondary learner containing several base-learners is designed as \( \Phi = (\phi)'_{i=1}^n \), where \( y_i = \phi(x'_i) \) and learns all samples in \( \mathcal{D}_\psi \).

(4) All the base-learners are combined and a stacking ensemble learner is established by certain strategy, as shown in Figure 2.

\[
\begin{align*}
\text{Sample Data Set} & \xrightarrow{\text{Training Sample Data}} \text{Primary Learner} \\
& \xrightarrow{\text{Sample Data 1}} \text{Base-learner 1} \\
& \xrightarrow{\text{Sample Data 2}} \text{Base-learner 2} \\
& \quad \vdots \\
& \xrightarrow{\text{Sample Data N}} \text{Base-learner N} \\
& \xrightarrow{\text{Integration Strategy}} \text{Ensemble Learner} \\
& \xrightarrow{\text{Test and Evaluate}} \text{Output Data Set} \\
& \xrightarrow{\text{New Input Data Set}} \text{Primary Learner} \\
& \xrightarrow{\text{Test and Evaluate}} \text{Output Prediction}
\end{align*}
\]

**Figure 2.** Basic framework of stacking ensemble learning model.

4. Flight path planning surrogate model

For aircraft’s sample data sets of ‘input parameters - output waypoint’ sequence, divide all the sample data sets according to certain characteristics into different groups, and then each group sample can be trained by base-learners using machine learning algorithm such as neural network, support vector machine (SVM), and so on. Afterwards, base-learners can be combined orderly by stacking method, establishing the direct mapping relation from the original input to the output, which helps to obtain the waypoint coordinates from flight mission parameters intelligently. The flight path planning surrogate model is established by following steps:

- Step 1: Based on path planning analytical model \( \Psi(\phi) \), a large number of samples are generated by setting different input parameters to obtain a sample data set \( \mathcal{P} \), and then the training data \( \mathcal{D} \) and test data \( \mathcal{T} \) are extracted from \( \mathcal{P} \).
- Step 2: For \( \mathcal{D} \) and \( \mathcal{T} \), take a series of data pre-processing operations, including data cleaning, data structuring, data normalization and other operations.
- Step 3: Group the data \( \mathcal{D} \) processed in step 2 twice. Firstly, all the samples are characterized by parameter \( c_i \), samples of the same \( c_i \) belong to the same group, which are used for training waypoint quantity learners. Secondly, all samples are characterized by parameter \( k \), samples of the same \( k \) belong to the same group, which are used for training waypoint coordinate learners.
- Step 4: For each group of samples in step 3, intelligent learning algorithm is used for training and then adjusting the parameters to construct each base-learner.
- Step 5: According to certain strategies, these base-learners are combined in order to form an integral surrogate model.
- Step 6: Test the integral surrogate model in step 5 with the test samples \( \mathcal{T} \), and return to step 4 to retrain base-learners if the errors does not meet the application requirements.

5. Examples and analysis

5.1. Example of flight path planning surrogate model
Based on engineering application, a case of flight path planning is simulated and it generates more than $1.2 \times 10^6$ group of samples. In all samples, the value of parameter $c_4$ can be 3, 4, 5, 6 or 7, and the value of parameter $k$ can be 4, 5, 6, 7, 8, 9, 10, 11, 12 or 13. Therefore, there are 5 base-learners in waypoint quantity learner named as Base-learner N3 to N7 and 10 base-learners in waypoint coordinate learner named as Base-learner P4 to P13. The surrogate ensemble model’s structure is shown in Figure 3.

5.2. Base-learner training algorithm

In this study, RBF (radial basis function) neural network is used for training each base-learner. RBF method is a technique for high dimensional interpolation. RBF neural network has excellent function approximation ability, accurate classification ability and fast learning rate. It obtains the norm of the input sample and the hidden layer point (centre point), and then bring it into the radial basis function. The corresponding output value can be obtained after multiplying it by the weight and summing all the nodes’ values. The structure of RBF neural network is shown as Figure 4, where $R$, $S^1$, $S^2$, IW, LW, $b^1$, $b^2$ are main calculating parameters. The neural network’s calculation process is as bellows:

$$n^1 = |IW - x| \cdot b^1 = \text{sqrt} \left\{ \text{diag} \left[ IW - \text{ones}(S^1, 1) \cdot x^T \right] \cdot IW - \text{ones}(S^1, 1) \cdot x^T \right\} \cdot \cdot b^1$$ \hspace{1cm} (2)

$$a^1 = \text{radbas}(n^1) = e^{-\left(n^1\right)^2}$$ \hspace{1cm} (3)

$$a^2 = \text{purelin}(LW \cdot a^1 + b^2)$$ \hspace{1cm} (4)

$$y = a^2$$ \hspace{1cm} (5)

Where IW, LW, $b^1$, $b^2$ will be trained after neural network’s iteration. After training each base-learner’s samples, flight waypoint coordinate can be calculated by formula (2) – (5) explicitly.
5.3. Results of example

According to the method in this paper, a flight path planning surrogate model was constructed, which was trained in MATLAB and developed in embedded environment to invoke the model. Each base-learner’s information is shown in Table 1 and Table 2. The neural networks’ training time is 158 minutes in total. The overall classification accuracy of waypoint quantity learner for $k$ values is over 99.999%, and the overall coordinate MSR (mean squared error) is about 0.000221° (about 20.1m in distance). The single call time of this flight path planning surrogate model in embedded environment is about 0.163s. The accuracy and real-time performance both meet the application requirements.

**Table 1.** Each base-learner’s information of waypoint quantity learner.

| Values of $c_4$ | Quantity of Sample | Training Result |
|-----------------|---------------------|-----------------|
| Original Sample | After Data Pre-processing | Base-learner | Classification Accuracy (%) | Training Time (s) |
| 3 | 243030 | 20097 | N3 | 99.999 | 1021.1 |
| 4 | 242801 | 20081 | N4 | 99.998 | 988.3 |
| 5 | 240808 | 20079 | N5 | 99.999 | 921.1 |
| 6 | 242837 | 20081 | N6 | 99.999 | 945.7 |
| 7 | 242641 | 20065 | N7 | 99.998 | 963.2 |
| Total | 1214117 | 100400 | - | 99.999 | 4839.4 |

**Table 2.** Each base-learner’s information of waypoint coordinate learner.

| Values of $k$ | Quantity of Sample | Training Result |
|-----------------|---------------------|-----------------|
| Original Sample | After Data Pre-processing | Base-learner | Coordinate MSR (°) | Training Time (s) |
| 4 | 350566 | 28990 | P4 | 2.21×10⁻⁴ | 1592.8 |
| 5 | 249459 | 20623 | P5 | 1.87×10⁻³ | 1032.4 |
| 6 | 180893 | 14956 | P6 | 1.42×10⁻⁴ | 544.5 |
| 7 | 226187 | 18706 | P7 | 1.56×10⁻⁴ | 797.3 |
| 8 | 102140 | 8448 | P8 | 2.05×10⁻⁴ | 368.1 |
5.4. Test the surrogate model

An example was used for testing the surrogate model in Section 5.3, whose input was \( x = [120.285, 30, 6.25, 5] \). The comparison of waypoint coordinate results calculated by analytic model and surrogate model were shown in Figure 5 and Table 3. After making statistics and analysis, the calculation time of analytic model was 5132.1 seconds and the calculation time of surrogate model was about 0.12 seconds. That is to say, the cost of calculation time was reduced significantly.

![Figure 5. Comparison of waypoint coordinate results.](image)

### Table 3. Waypoint coordinate values calculated by analytic model and surrogate model.

| Number of Waypoint | Longitude | Latitude |
|--------------------|-----------|----------|
|                    | Analytic Model (°) | Surrogate Model (°) | Analytic Model (°) | Surrogate Model (°) |
| 1                  | 120.176531 | 120.176536 | 30.017327 | 30.017322 |
| 2                  | 120.346733 | 120.346737 | 30.017357 | 30.017353 |
| 3                  | 120.373422 | 120.373426 | 30.017342 | 30.017344 |
| 4                  | 120.439254 | 120.439255 | 30.070637 | 30.070631 |
| 5                  | 120.531463 | 120.531463 | 29.995221 | 29.995227 |
| 6                  | 120.450346 | 120.450344 | 29.910839 | 29.910833 |
| 7                  | 120.381458 | 120.381452 | 29.954492 | 29.954490 |
| 8                  | 120.191981 | 120.191981 | 29.954494 | 29.954491 |
| 9                  | 120.187584 | 120.187581 | 30.049527 | 30.049525 |
| 10                 | 120.285005 | 120.285002 | 30.056206 | 30.056206 |
6. Conclusion
In this paper, a method based on stacking ensemble learning is introduced for establishing flight path planning surrogate model, in which several base-learners are trained for learning complex flight mission’s waypoints coordinates. It solves the problem of poor real-time performance of mathematical analytic model, as well as the problem of non-uniform dimension when learning all flight samples with a single learner. The surrogate model is relatively simple and easy to operate, fast in calculation and high in accuracy. In this method, the flight waypoint coordinates can be calculated accurately in real-time environment. At last, the method is proved highly effective through lots of tests.

References
[1] Singh V and Willcox K E 2017 Methodology for path planning with dynamic data-driven flight capability estimation AIAA Journal vol 55
[2] Schwartz K N, Pfaender H, Kirby M, Mavris D N, Stouffer V L, Kumer V, Trajkov S, Hasan S and Payan A P 2016 Initial feasibility test of exploring the air traffic management design tradespace through surrogate modelling Conf. on 16th AIAA Aviation Technology, Integration, and Operations Conference (Washington, D.C.)
[3] Othman N and Kanazaki M 2015 Surrogate model of aerodynamic model toward efficient digital flight Conf. on 2014 Asia-Pacific International Symposium on Aerospace Technology vol 99 (Shanghai, China) pp 703-712
[4] Divina F, Gilson A, Gomez-Vela F, Torres M G and Torres J F 2018 Stacking ensemble learning for short-term electricity consumption forecasting energies vol 11 p 949
[5] Sikora R and AI-Laymoun O 2015 A Modified Stacking Ensemble Machine Learning Algorithm Using Genetic Algorithms (University of Texas – Arlington, USA)
[6] Yang J J, Li J Q, Shen R F, Zeng Y, He J, Bi J, Li Y, Zhang Q Y, Peng L H and Wang Q 2016 Exploiting ensemble learning for automatic cataract detection and grading Computer Methods and Programs in Biomedicine vol 124 pp 45-57
[7] Sun W and Trevor B 2018 A stacking ensemble learning framework for annual river ice breakup dates Journal of Hydrology vol 561 pp 636-650
[8] Kwak J, Park J H and Sung Y 2017 Unmanned aerial vehicle flight point classification algorithm based on symmetric big data symmetry vol 9 p 1