Neural Network Classification-Regression Method Applied to Approach Speed Control Strategy

Mori, Ryota

(Citation)
Journal of Aerospace Information Systems,21(4):362-366

(Issue Date)
2024-04

(Resource Type)
journal article

(Version)
Accepted Manuscript

Neural Network Classification-Regression Method Applied to Approach Speed Control Strategy

Ryota Mori*
Kobe University, Kobe, 658-0022, Japan

I.Introduction

A stabilized approach is key to keep the aircraft safety during approach and landing. Almost half of aircraft accidents occur during approach and landing, with one of the major factors being the unstablized approach[1]. The unstabilized approach is also known as an unstable approach, and is defined as an approach when at least one of the stabilized approach criteria is not met. Flight parameters such as speed, altitude, and deviation from the nominal path must be maintained within certain pre-determined ranges at or below the stabilized point (either 500 ft or 1000 ft). If the approach is unstable, a go-around must be executed, but flight data statistics suggest that most unstabilized approaches continue to landings[2]. The number of unstailibzed approaches that continued to landings is much greater than the number of the go-around executed, and it is important to reduce the number of unstabilized approaches.

However, the unstailized approach is just the result, and it is important to identify the reasons of unstabilized approaches in order to reduce the number of unstabilized approaches. Therefore, there are many research approaches to tackle this issue. The energy management is said to be important for a safe landing, and has been applied to trajectory planning[3]. There are also many studies analyzing the relationship between energy history and aircraft stability using flight data of both commercial aircraft [4] and general aviation [5]. Apart from the energy management, unstabilized approach has been investigated by analyzing the eye-tracking[6], and several big data approaches have been proposed to identify unstabilized approaches[7]. Another study provides the real-time likelihood of unstabilized approach to the pilot[8]. The majority of these studies assume a single best (or nominal) approach, and the unstabilized approach is evaluated based on the deviation from this nominal approach.

Not all pilots follow the same control strategy which results in variations in approach profiles. The author argues that there are multiple nominal approach strategies which result in a safe landing. However, some of these strategies could be relatively unsafe, and it is important to identify and change such strategies. Such potentially hazardous strategies are often discussed via qualitative pilot comments, but such pilot comments often include subjectivity and ambiguity. Although pilot control strategies during approach cover various aspects, such as energy management, speed profile, and manual control, this study focuses on the speed profile during approach, and proposes to categorize and evaluate the speed profile quantitatively. The recommended speed profile during the approach is not always the same, and changes with the flight conditions such as wind in the air and on the ground, where a regression technique is required. In addition, as stated above, there could be multiple strategies of the speed profile control, and therefore a classification of the speed profile of each flight is also required prior to the regression. The existing machine learning methods such as a neural network (NN)[9] and clustering methods[10][11] are often used for either regression or classification, and are not intended to conduct classification and regression simultaneously. To address this issue, a new classification-regression method using NNs is proposed. The proposed method uses a NN as a regression method mainly, and the classification is achieved during the learning process, which achieves both a powerful classification and a regression. Using this proposed method, speed profiles during the approach are classified, and the characteristics of each classified group are investigated. The key contribution of this research is twofold. First, a new framework using NN to conduct simultaneous classification and regression is proposed. Second, the proposed modeling method is applied to an approach speed control problem, and several insights are obtained about the difference of approach speed control strategies. Note that this paper is an extended work of Ref. [12].

II.Proposed classification-regression method

In this paper, the author proposes to apply a NN to classification-regression problems. The NN is a machine learning method, and has a powerful classification and regression capability[9]. However, the normal NN can deal with either regression or classification only. This paper proposes a network structure shown in Fig. 1 to consider both

* Associate professor, Graduate School of Maritime Sciences, AIAA member.

classification and regression simultaneously. Each NN works as a regression model with a single output, so each NN creates a different output from the same input. In this example, three NNs are assumed, so three different outputs are created accordingly. Three outputs represent the speed profile of three types of strategies among pilots.

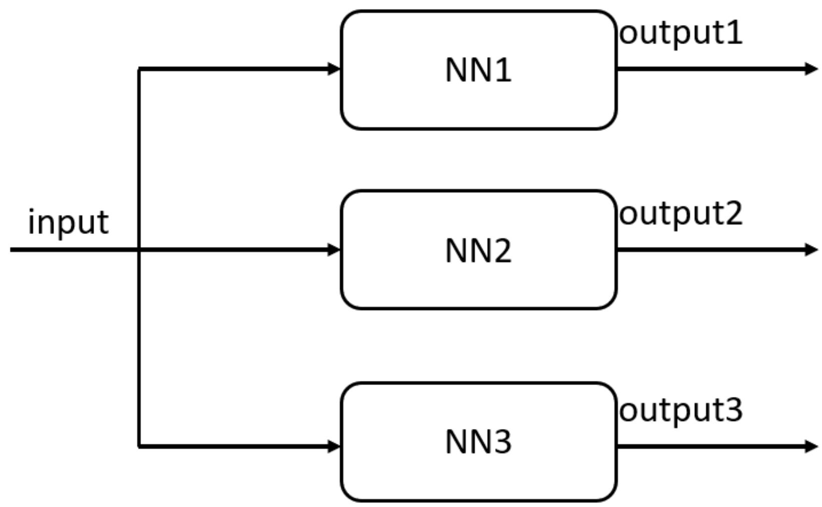

Fig. 1 Proposed network structure.

The biggest challenge of the proposed modeling is how to classify each flight to either group during the training process. In other words, how each flight is assigned to the appropriate NN during the training. In order to train NN as a regression tool, each flight must be classified in advance. To do that, the training process shown in Fig. 2 is proposed. The flight classifier classifies each flight to a NN by considering the difference between the actual labeled output (speed profile) and the calculated output (speed profile) of each NN. Once each flight is classified, each NN is trained using the flight data which belong to the NN. This classification-regression process is repeated until appropriate classification with sufficiently trained NNs is completed.

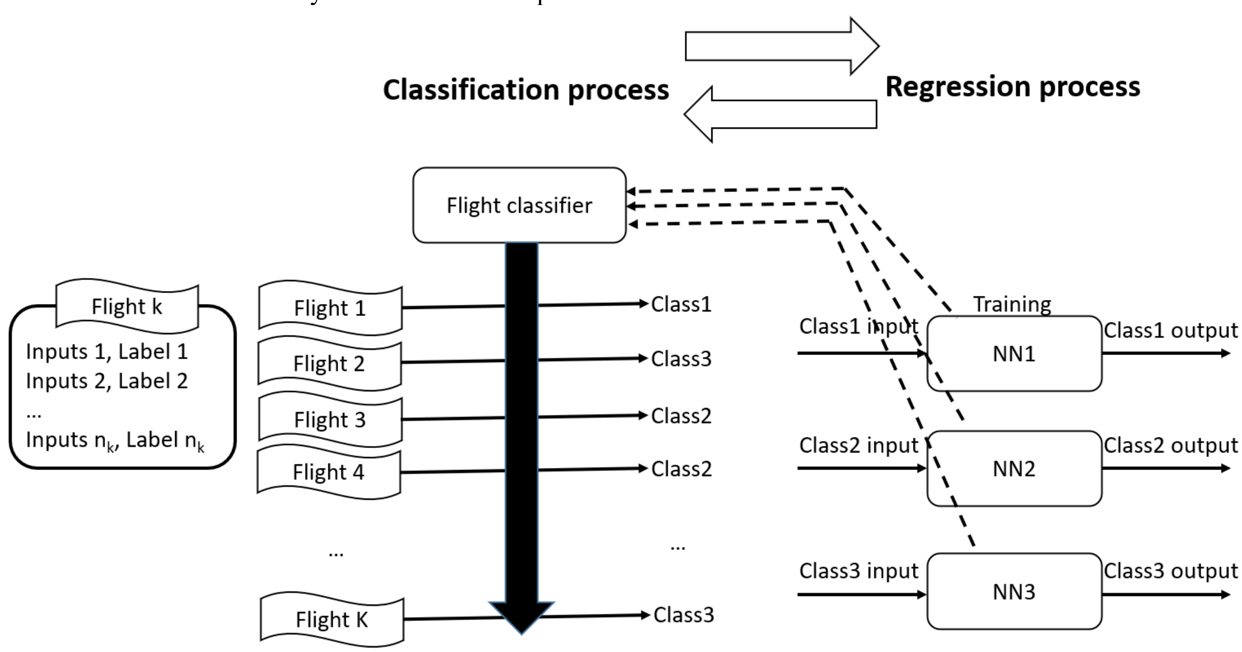

Fig. 2 NN training process using a flight classifier.

The flight classifier classifies each flight to either of three classes, and how each flight is classified is a key to successful NN training. The output error (e.g., RMSE) between the actual labeled output and each NN output can be used as a reference. However, the classification result during training must vary at the beginning, otherwise the initial classification result becomes the final classification result. To tackle this issue, the flight classifier is designed inspired by simulated annealing[13]. Simulated annealing is a heuristic optimization method, and is inspired by annealing in metallurgy. Simulated annealing is essentially a neighbor search algorithm, but the state moves more freely at the beginning (high temperature), which might negatively impact the solution. As time progresses (low temperature), the state becomes stable, and it moves only when the solution improves. In the same way, the classification is first more freely chosen at the beginning, and the classification becomes more stable later on. More specifically, the output error is calculated based on the following equation.

$$e_{k,m} = \frac{\sum_{j=1}^{n_m} |y_{j,m} - o_{k,j}|}{n_m} \tag{1}$$

where $y_{j,m}$ indicates the *j* th labeled output of the *m* th flight, $o_{k,j}$ indicates the *j* th output of the *k* th NN, $e_{k,m}$ indicates the mean absolute error (MAE) of the *m* th flight and *k* th NN, and n_m indicates the number of data set in *m* th flight. The lower output error means a better fit of the model. The selection of NN in flight classifier is randomly calculated to satisfy the following selection probability.

$$p_{k,m} = \frac{\exp\left(-\frac{e_{k,m}}{T_i}\right)}{\sum_{k=1}^{K} \exp\left(-\frac{e_{k,m}}{T_i}\right)} \tag{2}$$

$$T_i = \alpha^i T_0 \tag{3}$$

where $p_{k,m}$ is the selection probability of *k* th NN of *m* th flight, T_i is the temperature at *i* th iteration, and *K* is the number of NNs. When the temperature is high, $p_{k,m}$ is set more evenly regardless of the output error. When the temperature becomes small, high $p_{k,m}$ is set with lower output error. By using this process, the classification result gradually converges to the best one like the simulated annealing.

During this process, once each flight is classified, the NN training proceeds. This NN training runs with limited iterations only, and the NN output is changed slightly after the training. Once this limited training is completed, classification resumes. Since the classification includes the random process and the output of each NN is also changed by the training, the classification result is also likely to change every classification-regression process. This classification-regression process runs iteratively, and finally the sufficient training is completed with appropriate classification.

Each NN is a feedforward NN with two hidden layers. The details of NN are summarized in Table 1. These parameters are decided by trial-and-error using the flight data as well as created data sets where the classification results are known in advance so that the classification and regression results are stable among multiple runs. All flights are randomly split into 80 % training data and 20 % validation data to avoid over-fitting. The NN training is done by the training data only, and the NNs where the lowest output error of the validation data is obtained are used as a final result.

Note that the proposed method was first applied to several test functions, and the result shows that this method succeeded in both classification and regression.

Table 1 NN parameters.

NN parameters	Values
Activation function	ReLU
Number of hidden nodes	200, 200
Number of training iterations in each process	10
Number of classification-regression processes	500
Initial temperature	2.0
Final temperature	0.01
α	$(0.01/2.0)^{1/500}$
Batch size	512
Dropout rate	0.2, 0.2

III.Application to the speed profile control strategy

A. Problem setting and model structures

In this paper, the pilot speed control strategy during the approach is modeled by NNs. Here, the pilot speed control strategy is defined as the planned speed profile before the approach, and is assumed to be a function of the altitude. Once the planned speech profile is determined, the pilot has limited options to alter the profile. Since the planned speed profile is determined before the approach, the inputs of the NNs are set to the altitude and the flight conditions obtained prior to the approach. The proposed method is intended to model the planned speed profile. In the modeling process, the following assumptions are made: 1) the pilot speed control strategies can be classified into three types. 2) the descent speed history is affected by flight conditions and altitude. 3) the speed control strategy does not change within a single landing. 4) the planned speed profile and the actual speed profile are assumed to be the same. The factor 1) corresponds to the classification problem, i.e., the pilot strategies are classified by the descent speed history of each flight. The factor 2) corresponds to the regression problem, i.e., the input of the flight condition affects the output of the planned speed profile. The factor 3) can be used as a constraint of the classification. Since the output of the NN is the speed at every second, a single flight includes about 60 s time histories of outputs (speed profile) of a single NN model. As for factor 4), the planned speed profile and the actual speed profile do not match exactly, because the actual speed profile is affected by various factors such as wind, for example. However, the overall trend of the actual speed profile is not significantly different from the planned profile.

As for the flight environment, in particular, we consider ILS approach between 4000 ft and 200 ft. A Japanese aircraft operator has provided quick access recorder (QAR) data, which records aircraft detailed flight information (e.g., pitch angle, altitude, wind, and calibrated air speed (CAS)) every second. The analysis presented in this paper uses the QAR data of 390 flights of a single aircraft type. All flights in the data operated ILS approach. Since the aircraft descends at a constant descent angle (3 deg) during ILS approach, the dimension of the problem can be reduced and conclusions regarding pilot actions can be made by analyzing the speed profile over altitude only. Actually, the aircraft slightly deviates above or below the glideslope, and the speed is changed accordingly. However, the proposed method does not intend to model the speed profile in detail, but is meant to only capture the overall profile planned before the approach, so this assumption is appropriate.

As shown above, the output of the model is the descent speed at every second. As for the inputs, the following six inputs are chosen. All inputs and outputs are normalized so that the average is 0 and the standard deviation is 1.

1) Barometric altitude (above mean sea level)
2) Aircraft weight
3) Headwind component at 200 ft
4) Headwind component at 3000 ft
5) The maximum headwind change over the 12 s during the whole flight
6) Final approach speed

The barometric altitude is the main contribution to the speed decision during the descent, because the aircraft must reduce the speed to the final approach speed during the approach. The final approach speed itself is also determined in advance considering the various flight status such as aircraft weight and wind condition. The aircraft weight also affects the descent plan, because the acceleration/deceleration changes with the weight. The wind conditions, especially the headwind component, is also a key factor for the descent speed plan. Since the pilot knows the wind information only roughly in advance, so this time the headwind component at the ground (200 ft above ground level) and in the air (3000 ft above ground level) is included. The short-term wind change may also affect the speed plan, because the high-speed approach is more expected at gusty condition to avoid the stall. Therefore, the maximum value of wind change over the 12 s is included in the input, which is calculated in the following manner.

$$\max_{l} \frac{1}{12} \sum_{j=l}^{l+12} |w_{j+1} - w_j| \tag{3}$$

where w is the headwind component. During the approach of a single flight, all variables except barometric altitude are constant throughout a flight. Therefore, in this model, the speed profile is a function of the barometric altitude, and this profile is corrected by additional five inputs.

B. Modeling and classification results

Using these six inputs, the speed during the approach is estimated. Total 390 flights are split into five groups. Four groups are used for the training, and the rest of one group is used for the validation. There are five combinations of the training-validation data, so the training is conducted in each combination, and finally five NN sets are obtained.

Here, a NN set means trained three NNs in the proposed model. Each NN set has three NN groups named as: speed high (NN1), speed middle (NN2), and speed low (NN3).

Fig. 3 shows an example of the actual speed profile and the estimated speed profile in each group and each NN set. Since there are five NN sets, there are five different estimated result in each group. Each group shows slightly different results among NN sets, but overall, three different groups are created in all NN sets. In this example, NN2 fits the best to the actual speed profile, so this flight falls into the "approach speed middle". The output error defined in Eq. (1) is used as an index to determine the best-fitted group where the lowest output error is achieved.

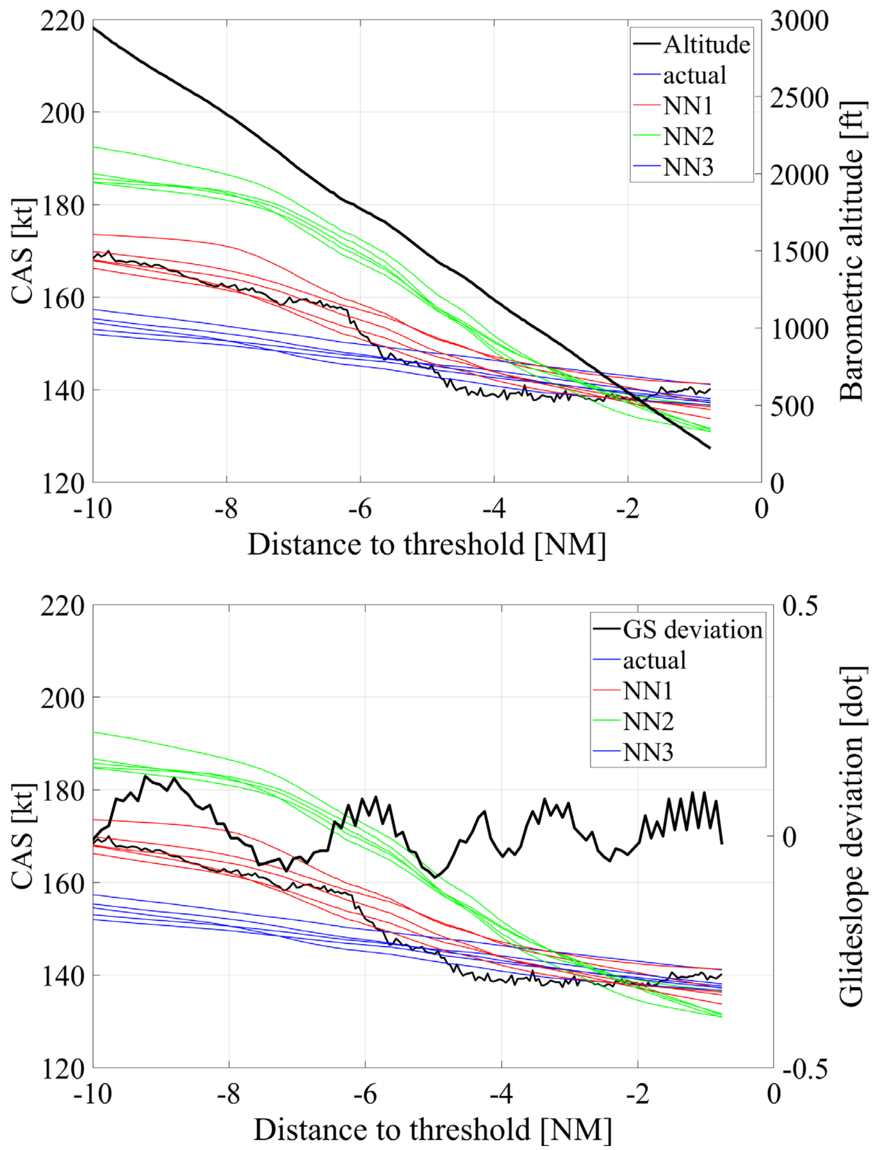

Fig. 3 Actual speed profile and estimated speed vs. altitude and glideslope deviation in each group for flight 1. (1 dot deviation corresponds to 0.375 deg.)

As seen in Fig. 3, the estimated speed within the same group slightly differs among NN sets, so the classification result can also differ among NN sets. Among 390 flights, 305 flights (78.2 %) show the same group in all five NN sets. As for the rest of 85 flights, at least three NN sets show the same group for all 85 flights, so the majority of the group can be determined in all flights. This is reasonable, because such a pilot speed strategy is not necessarily clearly classified, and some flights may fall into whichever of the two groups.

However, there are some flights where the output error is large with all NNs, which means that those flights are not well classified into any of NNs. The threshold of the output error is set to 5 kt, and if the output error is greater than 5 kt with all NNs, this flight is classified into either "speed very high" or "speed very low". Finally, all flights are classified into one of five groups: speed high (NN3), speed middle (NN2), speed low (NN1), speed very high, and speed very low. The number of flights in each group is summarized in Table 2. There are few approaches speed very low, so the statistical discussion may be difficult for these approaches speed very low.

Table 2 Number of flights in each classified group

Name of group	Number of flights
Speed very high	36
Speed high	98
Speed middle	131
Speed low	117
Speed very low	8

C. Classification result

Since all flights are classified into five groups, the characteristics of each group are investigated, which is a key contribution of this work. First, the relationship between the wind condition and the classified group is investigated. To quantify the strength of the wind turbulence, the headwind movement index is calculated by the following equation.

$$\frac{1}{n-1}\sum_{j=1}^{n-1}|w_{j+1}-w_j| \tag{4}$$

This is similar to Eq. (3), and calculated during the whole approach. The higher headwind movement index shows the stronger turbulence.

To evaluate the success of landings, stabilized approach criteria are used[2]. Although stabilized approach criteria include several aspects, here the following two aspects are used.

a. The aircraft is on the correct flight path.

b. Only small changes in heading/pitch are necessary to maintain the correct flight path.

This time, all 390 flights land safely, so there are no critical problems. However, in general, smaller deviation from the path and smaller pitch movement indicate better landings. Considering the fact that the speed profile mainly affects the pitch movement (not roll movement), two indices regarding glideslope deviation and pitch movement are defined, and the relative value of these indices are discussed.

First, the deviation from the path is discussed, which is evaluated by the highest glideslope deviation in each flight. Fig. 4 shows the average headwind movement index and the average highest glideslope deviation in each group. There are some trends observed. Apart from speed very high group, the headwind movement index is the lowest in the speed high group, and the highest in the speed very low group. The higher headwind movement index shows lower speed approach. The average maximum glideslope deviation among four groups is almost the same. The severer turbulence tends to cause the larger glideslope deviation, but it seems to be controlled by the selection of the appropriate speed profile so that the glideslope deviation is kept low. However, the exception occurs in the approaches speed very high. The headwind movement index is not smaller than that of approaches speed high, but is similar to the one in approaches speed middle or speed low. Correspondingly, the average maximum glideslope deviation is higher than other groups. The approach speed is relatively higher in the flights classified into speed high group than those in other groups, which seems to cause the high glideslope deviation.

Second, the change in pitch is discussed, which is evaluated by the pitch angle movement index calculated in the following expression.

$$\frac{1}{n-1}\sum_{j=1}^{n-1}|\phi_{j+1}-\phi_j| \tag{5}$$

where ϕ indicates the pitch angle. The large pitch movement index means the frequent oscillation of the pitch angle, so it is a good metric for landing stability; the lower pitch movement index is a better landing. The relationship between the average pitch movement index and the average headwind movement index in each group is shown in Fig. 5. Under the stronger turbulence, the pitch movement is expected to be larger, too. This trend is observed in four groups except the group of speed very high. However, the exception is the case in the speed very high group. The headwind movement is not large (similar to speed middle or low), but the pitch movement index is the highest. This large pitch movement is not caused by the wind turbulence, but seems to be due to the fact that the approach speed is too high.

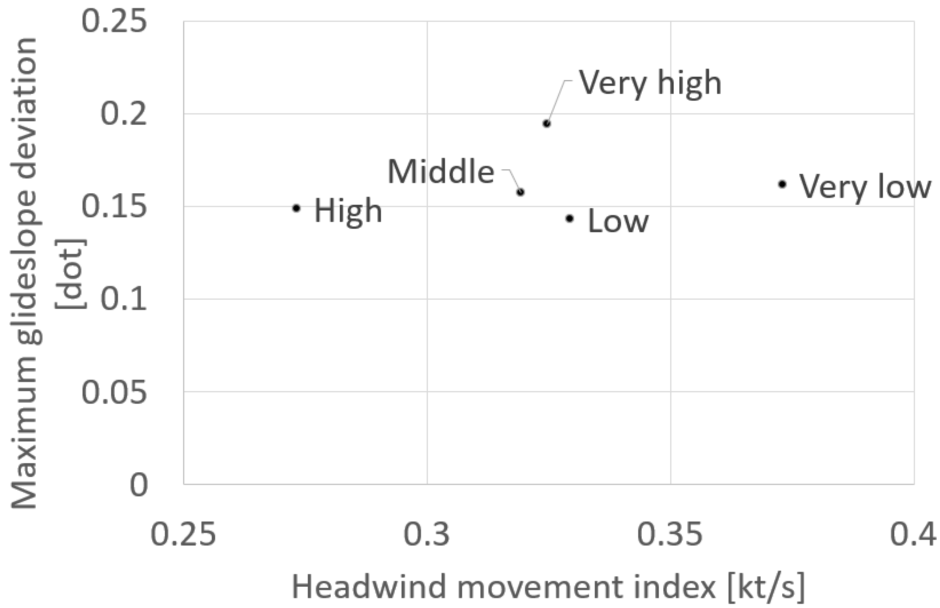

Fig. 4 Relationship between average headwind movement index and average maximum glideslope deviation in each group.

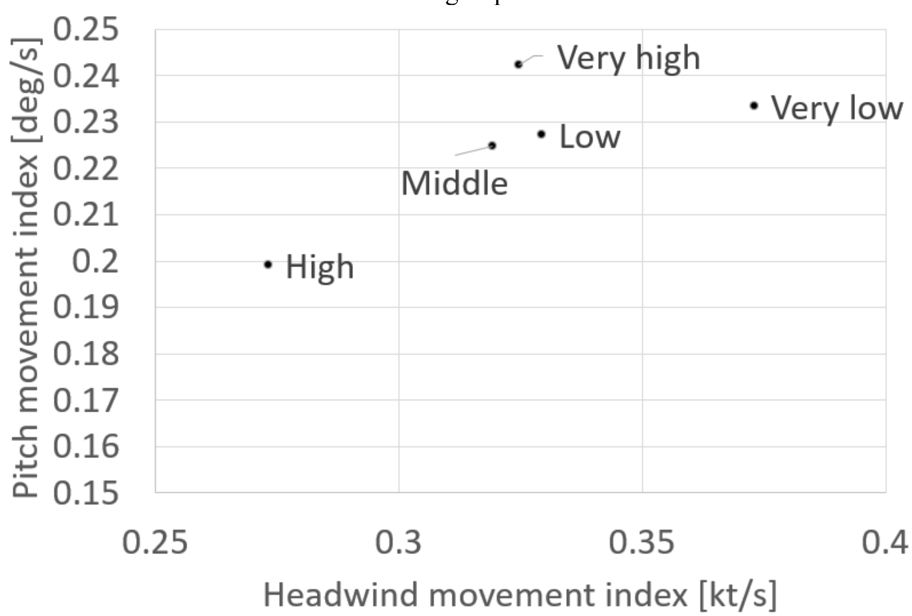

Fig. 5 Relationship between average headwind movement index and average pitch movement index in each group.

D. Classification result and pilot strategy

According to the classification result shown in the previous subsection, we can assume that there are five strategies. The main difference of speed profile among three groups (speed high, speed middle, and speed low) is observed in the initial speed at 3000 ft. The speed is mainly reduced to the final approach speed between 2000 and 1000 ft, and the final approach speed is maintained after passing 1000 ft. When the speed profile is largely deviated from all three groups, the strategy is classified into speed very low or speed very high. The pilots' selection process of these strategies is difficult to be investigated, but according to Fig. 4, higher approach speed is likely to be selected when the turbulence is relatively low except the speed very high group. Since the average maximum glideslope deviation is the same in all four groups (speed high, middle, low, and very low), only small differences to the stabilized approach criteria considered in this research are observed among these four strategies. Approaches high speeds are in general more fuel-efficient, so the pilot seems to choose the appropriate strategy considering the expected disturbance.

An exception is observed in the approaches speed very high. Both the glideslope deviation and the pitch movement index are relatively high considering the turbulence, which infers that this strategy (speed very high) is potentially dangerous. Although high speed approaches are not recommended, the proposed method can identify the threshold between “speed very high (potentially dangerous)” and “speed high (normal)”. The threshold changes with the flight conditions, but the appropriate threshold can be identified accordingly using the proposed method.

The reason why the speed very high is chosen is out of the scope of this paper because additional information is unavailable. A possible reason is that the pilot may make a wrong choice of the initial speed. If so, it is meaningful to identify such flights, and these pilots can recognize this fact. Another possible reason is the ATC instruction of the short-cut flight. If the short-cut is instructed, the aircraft has to reduce the speed for a shorter distance, which tends to cause the over-speed. Such an over-speed approach may be classified into approach speed very high.

IV.Conclusions

The stabilized approach is one of the key concepts to avoid aircraft accidents. In this paper, a new classification-regression method inspired by simulated annealing was proposed using NNs, which is applied to detect the potentially dangerous approaches. Under the same flight conditions, the speed profile becomes different due to the difference of pilot strategies, which was represented by the proposed method. The proposed method can estimate the speed profile of each strategy depending on the flight conditions, so the similar speed profile can be classified into different strategies depending on the flight conditions, which is difficult by simple inspection of the speed profile. The proposed method was applied to the approach data of 390 flights, and approaches speed very high showed the different trend from others and inferred to be potentially dangerous. Especially, the proposed classification-regression method can model a non-linear relationship with multiple groups, and the application will be universal.

Acknowledgment

This work was supported by JSPS KAKENHI Grant Number 22K04542.

References

[1] Boeing, “Statistical Summary of Commercial Jet Airplane Accidents, Worldwide Operations | 1959 – 2017”, 2018. https://www.boeing.com/resources/boeingdotcom/company/about_bca/pdf/statsum.pdf

[2] IATA, Unstable approach – Risk Mitigation Policies, Procedures and Best Practices 3rd edition, 2017.

[3] de Jong, P., de Gelder, N., Verhoeven, R., Bussink, F., Kohrs, R., van Paassen, M., and Mulder, M., “Time and Energy Management During Descent and Approach: Batch Simulation Study,” Journal of Aircraft, Vol. 52, No. 1, pp. 190–203, 2015.

[4] Gandhi, N., Richards, N., Bateman, A., Bolstad, C., Costello, A., “Pilot-in-the-Loop Demonstration of an Energy Monitor and Crew Alerting System,” AIAA Guidance, Navigation, and Control Conference, AIAA-2012-4819, 2012.

[5] Puranik, T., Jimenez, H., Mavris, D., “Energy-based metrics for safety analysis of general aviation operations,” Journal of Aircraft, 54(6), 2285-2297, 2017.

[6] Reynal, M., Rister, F., Scannella, S., Wickens, C., Hehais, F., “Investigating pilot’s decision making when facing an unstabilized approach: an eye-tracking study,” 19th International Symposium on Aviation Psychology, 335, 2017.

[7] Jiao, Y., Sun, H., Wang, C., HanProcedia, J., “Research on Unstable Approach Detection of Civil Aviation Aircraft” Procedia Computer Science, Vol. 131, pp. 525-530, 2018.

[8] Wang, Z., Sherry, L, Shortle, J., “Improving the Nowcast of Unstable Approaches,” 7th International Conference on Research in Air Transportation (ICRAT), 2016.

[9] Gurney, K., An introduction to neural networks, CRC press, 2018.

[10] MacQueen, J., “Some methods for classification and analysis of multivariate observations,” Proceedings of the fifth Berkeley symposium on mathematical statistics and probability, Vol. 1, No. 14, pp. 281-297, 1967.

[11] Ester, M., Kriegel, H. P., Sender, J., Xu, X., “A density-based algorithm for discovering clusters in large spatial databases with noise,” Proceedings of the Second International Conference on Knowledge Discovery and Data Mining, pp. 226-231, 1996.

[12] Mori, R., “Analysis of pilot operational strategy difference using neural network,” 32nd Congress of the International Council of the Aeronautical Sciences (ICAS 2021), 2021.

[13] Dowsland, K. A., Thompson, J., “Simulated annealing,” Handbook of natural computing, 1623-1655, 2012.