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Aircraft Type Recognition Based on Target Track

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Abstract. The target recognition plays an important role in air traffic management, and the research on automatic aircraft recognition is still in the exploratory stage. Since aircrafts move at high speeds in complex background, it is still a challenging task to quickly extract valid features from small amounts of data for aircraft type recognition. The machine learning is capable of capturing discriminating information and can well identify potential patterns from the dataset. Thus, we employ a novel classification model based on machine learning with the use of some effective motion features extracted from aircraft flight track information as the input of the model such as maximum speed, cruise speed, maximum acceleration, maximum climb rate. We performed experiments on datasets collected by multiple sensors and the results demonstrated the effectiveness of proposed model in significantly improving the aircraft type recognition accuracy, especially for military aircrafts. Besides, the model avoids the inherent deficiencies of graphics and image processing, and can well meet the needs of the air traffic management.

1. Introduction

With the increasing types and numbers of aircrafts, the ability to reliably recognize aircraft type is a vital aspect of air traffic control in both daily life and modern battlefield. At present, in order to achieve a better recognition accuracy, the work of aircraft type recognition still needs a great deal of human experience and consumes a lot of time and other manpower resources. A common technique for identification of military aircraft is Identification Friend Foe (IFF). Civilian aircraft use a technique similar to IFF called Secondary Surveillance Radar (SSR)[1]. The fundamental drawback of techniques like IFF and SSR is that they require active cooperation of pilots which makes these techniques less efficient and less practical. The research on automatic aircraft recognition is still in the exploratory stage, and most of the existing work is based on graphic image processing[2-5]. Aircraft recognition based on image contour is mainly to find the approximate invariant features[6-8]. Commonly used invariant feature extraction methods include Hu matrix[7], affine distance, Fourier descriptor[9], wavelet moment, and Zernike moments. Radar signals are also widely used in air traffic control[1]. Both radar-based and image-based methods make use of the distinctions of aircraft contour to identify the type of the planes. However, in practice, these methods face many challenges: 1. The overall shapes of the aircraft are generally similar, especially for a wide range of civilian aircrafts. 2. The aircraft's shape is highly dependent on the orientation and distance of the aircraft with respect to the sensor. 3. It is difficult to take a clear picture of an aircraft moving in high speed. 4. Image quality is heavily constrained by the weather and other natural factors. These challenges make the identification method based on contour information more difficult to achieve in practical application.
To overcome these serious drawbacks, we employ a novel classification model based on machine learning with the use of some effective motion features, such as maximum speed, cruise speed, maximum acceleration, maximum climb rate, extracted from aircraft flight track information as the input of the model. Different from extracting contour invariants during aircraft movement, we extract dynamic characteristics during the movement which can well avoid the shortcomings mentioned before. This model has several obvious advantages: 1. Motion features have strong representation, and identifying aircraft type by its set characters on movement is closer to the real needs. 2. It is easier to extract dynamic motion features than invariant features in a dynamic process[10], and the model of a single aircraft’s movement can be reduced to a movement model of a probe point which can greatly reduce the computational complexity, speed up the recognition process and increase the ability to quickly handle the task of identifying a large number of targets. 3.Since most aircrafts fly on fixed routes, by combining with the track information, our model makes good use of the historical experience and knowledge, and can obtain higher accuracy on civilian aircrafts whose shape and movement characteristics are very similar.

2. Basic approach

2.1. Data collection and preprocessing

Our datasets are based on the time-series data of aircraft flight track collected by multiple sensors including the detecting time $t$, longitude $Lng$, latitude $Lat$, altitude $H$, velocity $V$, heading $Di$, sensor signal type $Sg$ and aircraft type label $Label$. And the aircraft type labels are manually marked according to expert's experience. Here we think there is no error in the marked labels.

2.2. Feature extraction

Due to the differences in aircraft motion performance and pilot’s flying habit, we can extract useful features as the input of the recognition model based on historical track. Wang M[11] discussed nine motion performance features that may affect the aircraft type recognition, but some of them are complicated to calculate and require high precision of the acquisition sensor. Therefore, in this paper, four motion features were extracted from the flight data: maximum speed, cruising speed, maximum acceleration, maximum rate of climb.

**Maximum speed:** Aircraft reached the maximum speed when the booster was at maximum thrust. At the maximum speed, the tail of the airplane cannot be heat balanced and this state cannot last long. In our data set, we will approximate the detected instantaneous maximum speed as the maximum speed of the aircraft.

$$V_{k\text{max}} = \max_{i} V_{ki}$$  \hspace{1cm} (1)

Where $k$ is the number of the aircraft in the detection record and $i$ is the ith detection time point.

**Cruising speed:** Also called as economic speed, when the aircraft did not open afterburner, the aircraft can stay in the air the longest time in this state and the tail of the airplane can reach thermal equilibrium. We approximate the average speed of the probe to the cruising speed of the aircraft.

$$\bar{V}_{k} = \frac{\sum_{i=1}^{n} v_{ki}(t_{k(i+1)} - t_{ki})}{t_{kn} - t_{k1}}$$  \hspace{1cm} (2)

Where $n$ is the number of probe records of aircraft $k$.

**Maximum acceleration:** The maximum capacity of the aircraft to enhance speed. The magnitude of the acceleration is related to the propeller's power, shape and cooling capacity of aircraft. Therefore, the ability of acceleration is an important parameter that reflects the characteristics of different types. We calculate the difference of velocity in each probe interval as the value of acceleration and choose the maximum value as the maximum acceleration characteristic of the aircraft.

$$a_{kv\text{max}} = \max_{i} \frac{v_{k(i+1)} - v_{ki}}{t_{k(i+1)} - t_{ki}}$$  \hspace{1cm} (3)
**Maximum rate of climb:** The maximum rate of climb reflects the ability of the aircraft to overcome its gravity and resistance and is one of the characteristics that can best reflect the kinematic performance of the attack aircraft. In the flight track information, the maximum value of altitude difference in the detection interval is considered as the maximum rate of climb (RoC).

\[
\text{RoCmax} = \max_i \frac{h_{k(i+1)} - h_{k(i)}}{t_{k(i+1)} - t_{k(i)}}
\]  

(4)

Since most aircrafts have a fixed route, we consider the longitude, latitude, altitude, velocity, heading information, sensor signal types together with the above four characteristics as the inputs of our recognition model.

2.3. Aircraft type recognition model using machine learning

The architecture of the proposed recognition model is demonstrated in Figure 1. The input of the model are the selected features. The classic algorithms in machine learning including SVM[12, 13], ELM[14-16] and RKELM[17] are used respectively in our model as the classifier. The output of the model is the type of aircraft.

![Figure 1. Proposed aircraft recognition model](image)

3. Experiments and results

3.1. Datasets

We conducted experiments on four different datasets respectively: dataset 1 covers 3 classes of 26309 samples; dataset 2 covers 4 classes of 10928 samples; dataset 3 covers 7 classes of 3020 samples; dataset 4 covers 10 classes of 3910 samples. The dataset 1 is collected from civilian aircrafts of the Boeing Company, Airbus and Bombardier respectively. The dataset 2 is also collected from civilian aircrafts. The dataset 3 is collected from military aircrafts, while data set 4 contains both track information of military and civilian aircrafts. As part of the data is classified, we use numbers to indicate the types of aircraft. Figure 2 shows the category distribution of these four datasets.
3.2. Methodology

All datasets are divided into training set (70%) and test set (30%), and all the datasets are processed in two ways. One way does not extract the motion characteristics from the flight data, which takes track information directly as the input of the model. The other way adds the extracted motion features to the original data, and then the recognition model takes this data as input. The coefficient correlation matrix showed the correlation among all the features and the aircraft type. As can be seen in Figure 3, the relative high correlation between the movement characteristics we extracted and the aircraft type indicates that the movement characteristics make a positive contribution to the aircraft type recognition. The significant correlation between the longitude and the type of sensor signal is due to the difference in geographic location of the sensors.

For the classical ELM algorithm, we use the Hardlim function as the activation function.

$$\text{hardlim}(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{otherwise} \end{cases}$$

(5)

For RKELM algorithm, the Gaussian kernel function has been used in the experimental study.

$$k(x, x_i) = \frac{\exp\left(-\frac{||x-x_i||^2}{\sigma}\right)}{\sigma}$$

(6)

For SVM algorithm, Gaussian kernel function has also been considered in experiment.

$$k(x, x_i) = \exp\left(-\gamma ||x - x_i||^2\right)$$

(7)

In addition, all the results reported are the average of 20 independent trials. For ELM and RKELM networks, the number of hidden nodes $l$ is chosen by cross-validation method with step size 10, and only the obtained optimized $l$ is reported. In order to achieve better generalization performance, the parameters of the model need to be properly selected. After a large number of experiments, we choose the parameter values shown in Table 1.
3.3. Performance evaluation

Because there is no obvious category imbalance in our dataset, the accuracy on the test sets was employed to measure the performance of the model. Some interesting remarks can be drawn from Table 2. Firstly, compared with the group without the extracted features, it is possible to observe that the testing accuracy has been significantly improved by adding the extracted motion features. In dataset 1, the testing accuracy of ELM was improved by 22.21%, RKELM outperformed with 17.74% improvement, SVM outperformed with 14.77% improvement. In dataset 2, the testing accuracy of ELM was improved by 12.69%, RKELM outperformed with 11.40% improvement, SVM outperformed with 10.85% improvement. In dataset 3, the testing accuracy of ELM was improved by 15.38%, RKELM outperformed with 6.92% improvement, SVM outperformed with 9.19% improvement. In dataset 4, the testing accuracy of ELM is improved by 16.63%, RKELM outperformed with 11.32% improvement, SVM outperformed with 9.56% improvement. Meanwhile, the training time did not increase significantly. Secondly, the model using SVM algorithm has a significantly better recognition effect on all data sets than the other two algorithms. Since our data volume is small, the disadvantages of SVM in training time are not obvious. When facing a larger training data set, RKELM algorithm can achieve faster training speed and high prediction accuracy. The experimental results are shown in Table 2.
In the meantime, it was found that our model gives better performance for the recognition of military aircraft. This means that our model may have a broad application prospect in the future informationized battlefield.

Table 2. Average recognition accuracy on datasets

| Dataset | No motion features added | Motion features added |
|---------|--------------------------|-----------------------|
|         | ELM | RKELM | SVM | ELM | RKELM | SVM |
| 1       | 60.60% | 74.59% | 81.58% | 82.81% | 92.34% | 96.35% |
| 2       | 69.71% | 81.79% | 87.77% | 82.41% | 93.19% | 98.63% |
| 3       | 74.78% | 88.75% | 89.82% | 90.16% | 95.67% | 99.02% |
| 4       | 72.23% | 85.21% | 89.58% | 88.86% | 96.53% | 99.14% |

4. Conclusion
As an important technology in air traffic management, aircraft type recognition is gaining more and more attention by scholars. The existing researches have been mostly based on graphic image processing, which is inherently deficient in the high dynamic real-time air combat. We employ a novel classification model based on machine learning with the use of some effective motion features extracted from aircraft flight track information as the input that automatically identifies aircraft type. Experimental results show that the model has a good recognition effect, especially for military aircraft. The model avoids the inherent deficiencies of graphics and image processing, so it will well meet the needs of the air traffic management and has a wide range of application in modern battlefield.

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References
[1]  Proefschrift A, Zwart J P, Gelsema I S J, et al. Aircraft Recognition from Features Extracted from Measured and Simulated Radar Range Profiles [J]. Universiteit Van Amsterdam Uva, 2003,
[2]  Somaie A A, Badr A, Salah T. Aircraft recognition system using eigenvector technique; proceedings of the Radio Science Conference, 1999 NRSC ’99 Proceedings of the Sixteenth National, F, 1999 [C].
[3]  Liu Y. Aircraft type recognition based on convex hull features and SVM [J]. Proceedings of SPIE - The International Society for Optical Engineering, 2007, 6786(
[4]  Hsieh J W, Chen J M, Chuang C H, et al. Aircraft type recognition in satellite images [J]. IEEE Proceedings - Vision, Image and Signal Processing, 2005, 152(3): 307-15. 
[5]  Kamgar-Parsi B, Kamgar-Parsi B, Jain A K. Automatic aircraft recognition: toward using human similarity measure in a recognition system; proceedings of the Computer Vision and Pattern Recognition, 1999 IEEE Computer Society Conference on, F, 1999 [C].
[6]  Dudani S A, Breeding K J, Meghee R B. Aircraft Identification by Moment Invariants [J]. IEEE Transactions on Computers, 1977, C-26(1): 39-46.
[7]  Rong H J, Jia Y X, Zhao G S. Aircraft recognition using modular extreme learning machine [J]. Neurocomputing, 2014, 128(5): 166-74.
[8]  Li X D, Pan J D, Dezert J. Automatic Aircraft Recognition using DSmT and HMM; proceedings of the International Conference on Information Fusion, F, 2014 [C].
[9]  Wallace T P, Wintz P A. An efficient three-dimensional aircraft recognition algorithm using normalized fourier descriptors * [J]. Computer Graphics & Image Processing, 1980, 13(2): 99-126.
[10] Chu W, Liu L. Research and Simulation Implementation of Airplane Target Typical Motion Model; proceedings of the International Conference on Computational and Information Sciences, F, 2013 [C].

[11] Wang M. Research on the Recognising the Kind and Type of A Plane by It's Characters on Movement [J]. Computer & Digital Engineering, 1999,

[12] Sain S. The Nature of Statistical Learning Theory [J]. Technometrics, 1997, 8(6): 409-.

[13] Suykens J A K, Vandewalle J. Least Squares Support Vector Machine Classifiers [J]. Neural Processing Letters, 1999, 9(3): 293-300.

[14] Huang G B, Zhu Q Y, Siew C K. Extreme learning machine: a new learning scheme of feedforward neural networks; proceedings of the IEEE International Joint Conference on Neural Networks, 2004 Proceedings, F, 2005 [C].

[15] Huang G B, Zhu Q Y, Siew C K. Extreme learning machine: Theory and applications [J]. Neurocomputing, 2006, 70(1): 489-501.

[16] Huang G B, Chen L, Siew C K. Universal approximation using incremental constructive feedforward networks with random hidden nodes [J]. IEEE Transactions on Neural Networks, 2006, 17(4): 879.

[17] Deng W Y, Ong Y S, Zheng Q H. A Fast Reduced Kernel Extreme Learning Machine [J]. Neural Networks, 2016, 76(C): 29-38.