Aircraft Type Identification Using Reinforcement Active Learning

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Abstract. As a subclass of Automatic Target Recognition problem, Automatic Aircraft Recognition plays an important role in air traffic management and modern battlefield for automatic monitoring and detection. 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 of fast data processing and accurate aircraft type recognition. Besides, active learning has recently attracted many researcher’s interesting. Based on this, we employ a learning-based approach which combines active learning with reinforcement learning to learn how and when to request labels for the aircraft type recognition problem. The experimental results show that the model can achieve a good prediction accuracy with few label requests.

Introduction

 Nowadays the types and numbers of aircrafts are increasing quickly, so the ability to recognize aircraft type accurately is a vital aspect of air traffic control not only in daily life but also the modern battlefield. At present, in order to achieve a better identification accuracy, the work of aircraft type identification still needs a great deal of human experience.

 Usually the way to deal with small data sets is using the expert experience to give high-confidence data annotation. However, taking time cost and labeling overhead into account, this ground truth labeling is no longer viable as the data size increases dramatically. Under this circumstance, semi-supervised learning and active learning algorithms have emerged and developed rapidly, and become an important technology to deal with unlabeled examples. Although both of them use unlabeled and labeled instances to train a highly accurate classifier to reduce the workload of human experts, the active learning algorithm simulates the human learning process, selects part of instances to label and join the training set, and iteratively improves the generalization performance of the classifier.

 The stage of research on automatic aircraft identification is still exploratory now, most of the existing work is based on graphic image processing\cite{1-4}. Radar signals are also widely used in air traffic control\cite{5}. Both image-based and radar-based methods make use of the distinctions of aircraft contour to identify the type of the planes. However, these methods face many challenges\cite{6}: 1. Image quality is severely constrained by weather and other natural factors. 2. The overall shapes of the aircraft are generally similar, especially for a wide range of civil aircrafts. 3. It is difficult to take clear pictures when the plane is flying at high speed. 4. The shape of the aircraft is highly dependent on the direction and distance of the aircraft relative to the sensor. These challenges make the identification method based on contour information more difficult to implement in practical applications. To overcome these serious drawbacks, we employ a novel classification model based on reinforcement active learning by using some effective motion features as the input of the model, such as maximum speed, cruise speed, maximum acceleration, maximum climb rate, which are extracted from aircraft
flight track information. Different from extracting contour invariants during aircraft movement, the benefit of extracting the dynamic characteristics during the movement is that it can well eliminate the shortcomings mentioned before.

Most of the traditional active learning methods are carefully formulating some criteria for selecting samples, such as uncertainty sampling[7], query-by-committee[8], margin[9] and representative and diversity-based sampling[10]. It's hard to judge which approach is better, because each approach starts from a reasonable, meaningful and completely different motivation. At the same time, there is no all-purpose method that perform best on all datasets. Inspired by the fact that humans can learn new classes from a single instance[11], our goal is to design an artificial intelligence agent that has the capability to avoid requesting classification labels too often[12]. Here we introduce a learning-based approach rather than a hand-designing criterion, a model that learns active learning algorithms via reinforcement learning[13, 14]. This method can not only learn to classify instances using small supervision but additionally learn a label query strategy. And our model falls into the class of stream-based active learners which considers the online setting of active learning. It is a natural fit for an active learner using reinforcement learning to solve a continuous decision problem since each query action affects the next decision (when and which instance to query based on the state of the basic learner). In this way, the active query system trained by the reinforcement can learn a cogent, non-myopic strategy[15] and can make effective decisions with small supervision.

Our primary contribution is firstly using the active one-shot learning model in aircraft type identification problem. Our model is mostly inspired by Mark Woodward et al[16], whose work is considered as the first application of reinforcement learning with deep recurrent models to the task of active learning. And with the use of some effective motion feature our model has several obvious advantages: 1. The motion features have strong representation, and the aircraft type is identified by its set motion characteristics closer to the actual needs. 2. In the dynamic process[17], extracting dynamic motion features is easier than extracting invariant features. The motion model of a single aircraft can be simplified to the motion model of the probe points, which greatly reduces the computational complexity. 3. Since most aircraft fly on fixed routes, combined with track information, our model can achieve higher accuracy for civil aircraft with very similar shape and motion characteristics.

We evaluate the model on dataset of airplane target tracks collected by multiple sensors, and experiment results show that our model can learn efficient label querying strategies. We demonstrate empirically that our model can achieve better performance and learn a query strategy based on uncertainty in an end-to-end fashion. For active learning, it means significantly reducing the workload of human experts.

Related Work

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)[5]. 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. Aircraft identification based on image contour is mainly to find the approximate invariant features[18-20]. Commonly used invariant feature extraction methods include Hu matrix[19], affine distance, Fourier descriptor[21], wavelet moment, and Zernike moments.

Reinforcement learning has received widespread attention in these years. The method can interact with the environment and provide good approximation of objective values based on relevant feedback. It is theoretically very suitable for online, real-time prediction and decision making. Especially for specific complex tasks, in an unknown environment, reinforcement learning can learn optimal strategies by exploring sampling. The successful application of reinforcement learning has been well implemented in the prediction and control of complex virtual environments.[13]. However, as Alex Irpan explains on his blog[22], there are still many limitations to reinforcement learning in the
face of practical problems. A fatal flaw in pure reinforcement learning method is reinforcement learning sometimes may be horribly sample inefficient. To solve this problem, the idea of adding a fair amount of expert experience came into being.

In this article, we mainly consider the setting of the single pass stream-based online active learning in aircraft identification. Most of existing methods have relied on heuristics, such as similarity measures between current instances, the instances seen so far[23], or uncertainty metrics in label prediction[23, 24]. Different from engineered selection heuristics, we introduce a model learning active learning algorithms end-to-end in an reinforcement learning way. Some recent researches have had similar inspiration. Woodward & Finn[16] first combined reinforcement learning with active learning. Bachman et al.[25] and Pang et al.[15] introduced a pool-based active learning algorithm through meta-learning. The same idea is applied to the artificial intelligence classification systems by Puzanov & Cohen[12]. In our work, a deep recurrent neural network[26] function approximator is used to represent the action-value function.

Basic Approach

Data Collection and Preprocessing

Our dataset is based on the time-series data of civilian 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 ground truth aircraft type labels are marked by the oracle according to expert's experience.

Feature Extraction

Due to differences in aircraft performance and pilot flight habits, we can extract useful features as input to a historical trajectory-based recognition model. Four motion features were extracted from the flight data[6]: maximum speed, cruising speed, maximum acceleration, maximum rate of climb.

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

Task Description and Methodology

In this section, we employ a model termed the reinforcement one-shot active learning (AOL) framework, introduced by Mark Woodward et al. (2016)[16], to achieve the active aircraft type recognition, as depicted in Fig. 1, where a long short-term memory (LSTM), which is connected to a linear output layer, is used to approximate the action-value function. Next, the specific algorithm is given.

At each time step of the episode, the model receives an instance $x_t$, and need to decide to execute an action. Assume that in each episode, there are up to $M$ possible classes. Let $a_t$ be the action at timestep $t$, so the action space is defined as follows:

$$A = \{c_1, \ldots, c_M, a_{req}\} \quad (1)$$

The action is $a_t = c_i$ when the instance is classified under category $i$ at time $t$. The action is $a_t = a_{req}$ when a query is needed. $a_t$ is a one-hot vector which consists the optionally predicted label $\hat{y}_t$ following by a bit for requesting the label. The model can only performe one action at a single timestep. If the label of instance $x_t$ is required, then no prediction will be made, and the true label $y_t$ of the instance will be send into the model at next observation $x_{t+1}$ along with a new instance $x_{t+1}$. If a prediction is decided to make, then no request will be made and a $\hat{y}_t$ will be included in the next observation instead of the true label.
is the reward received after action $a_t$ in state $s_t$, and $\gamma$ represents the discount factor for future rewards. At each time step, one of three rewards is given depending on the action it choose: $R_{\text{cor}}$ for correctly predicting the label, $R_{\text{inc}}$ for incorrectly predicting the label, $R_{\text{req}}$ for requesting the label. The aim is to maximize the sum of rewards received in this episode.

$$r_t = \begin{cases} R_{\text{cor}}, & \text{if predicting and } \hat{y}_t = y_t \\ R_{\text{inc}}, & \text{if predicting and } \hat{y}_t \neq y_t \\ R_{\text{req}}, & \text{if a label is requested} \end{cases}$$

(2)

Figure 1. Task structure.

**Experimental Results**

Now we represent the results of the experiments of our model. In the experiment, we train the model on the dataset of civilian aircraft flight tracks collected by multiple sensors and extracted the motion features as the inputs of the model. The dataset covers 78 classes of aircrafts, each class consists of 20 aircrafts, giving 1560 total aircrafts. We randomly divided the dataset into 54 classes for training and keep the rest 24 classes for testing. Our model interacts with classes of characters it did not encounter during training to measure its test performance.

In each episode, 30 aircraft flight tracks were randomly selected from 3 randomly sampled classes, without replacement. Here, the number of samples from each class may not be balanced. Each selected class in the episode was assigned to a random label which was represented by a slot in a one-hot vector of length 3, giving $y_t$. An LSTM with 400 hidden units was used here. We optimized the parameters of our model using Adam with the default parameters[27]. During training process, epsilon greedy exploration with $\epsilon = 0.3$ is used for actions selection. The learning rate of training was set to 0.002 and the discount factor $\gamma$ was set to 0.5. The reward values were set as: $R_{\text{cor}} = +1$, $R_{\text{inc}} = -1$, and $R_{\text{req}} = -0.3$.

During training, the 1st, 2nd, 5th, and 10th instances of all classes in each episode are identified. It should be noted that in this analysis the method we use to calculate the accuracy is treating label requests as incorrect label prediction. After training on 1,000,000 episodes, training is ceased. Then the model was given 100,000 more test episodes. In these episodes, no further update occurred, and the model was to run on never-before-seen classes pulled from a disjoint test set. We report the results in Fig. 2 and Fig. 3.
As can be seen in the plot, our model learns to query the label for early instances of a class, and make more prediction for later instances. At the same time, the accuracy of the model is improved on later instances of a class. This is an important evidence of successful achieving the intelligent recognition of aircraft type obtained with the use of the active one-shot learning model based on deep reinforcement learning.

Figure 2. Label requests(a) and accuracies(b) per episode for the 1st, 2nd, 5th, and 10th instances of all classes.

Figure 3. Overall request (a) and accuracy (b) results.

**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. In this paper, first, we employ an active aircraft type recognition 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. Second, we introduce a one-shot learning model in an active-learning set-up for aircraft type recognition based on deep reinforcement learning to learn when and how to predict aircraft type or require the true label. And the experimental results show that the model has a good recognition effect, and what is more, the proposed model can learn how to label examples and when to instead request a label, especially for military aircraft, so it will well meet the needs of the intelligent air traffic management and has a wide range of application in modern battlefield.
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