Research on UAV Signal Classification Algorithm Based on Deep Learning

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ABSTRACT

*With the continuous development of Unmanned Aerial Vehicle (UAV) technology and its industry, the detection and recognition technology of UAV have attracted the attention of researchers. In this paper, the author focuses on the defects and deficiencies of traditional radar, visual and acoustic UAV detection technology. Considering that the UAV's own radio communication signal can be used for detection, a UAV signal classification method based on deep learning is proposed. This algorithm can extract the characteristics of UAV Communication Law, so as to achieve the target classification. The experimental results show that the average recognition rate of UAV is 95% in the test, and the recognition rate of most types of UAVs is more than 98%. In addition, the classification rate for the flight attitudes of UAVs can reach more than 95%. Therefore, it can be concluded that the classification algorithm designed in this paper can effectively meet the needs of UAV detection and recognition in the actual scene.

CCS CONCEPTS

• **Computing methodologies**; • **Machine learning**; • **Machine learning approaches**; • **Neural networks**;

KEYWORDS

UAV classification, Communication awareness, LSTM, Deep learning network

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1 INTRODUCTION

In recent years, UAV technology has developed rapidly. Under the continuous research and the efforts of a series of civil UAV manufacturers like DJI Company, the cost of UAV has declined, and the performance has been improved. Additionally, the endurance mileage continues to increase, and all kinds of applications emerge one after another. The UAV has gradually changed from the traditionally and expensively professional small unmanned flight equipment to personal aerial photo-taking or aircraft toys that the general public can afford, so that people can take aerial photography and play anytime and anywhere. However, with the rapid development, there are more and more UAVs in the airspace at present. These large numbers of unmanned UAVs could bring huge security risks to airport areas, military secret areas and dense passenger flow areas. To solve the problems, various drone manufacturers need to restrict the illegal use of drones by setting no-fly zones and other means through the software. In addition, relevant airports and military zones are also required to improve their ability to detect targets. Therefore, with the rise of the UAV industry, a large number of researchers have carried out studies on the detection technology of drones.

However, the development of UAV detection system is restricted due to the lack of open source database of UAV RF signals. In the study of Al-Sa'D et al.[1], they proposed a point that UAV can be detected and identified by using communication perception technology, which is based on the communication law between UAV and remote control and graphics transmission equipment. They built a set of UAV wireless control signal acquisition platform to collect all kinds of UAV communication data. The corresponding database is also established and the deep learning algorithm is used to learn and classify these data. While the ADC data and time-frequency domain data collected are too large, which contains a lot of redundant information, the direct use of the algorithm is too complex, leading to performance degradation. Therefore, this paper puts forward an idea that the data can be preprocessed according to its own characteristics, and then could be replaced into the deep learning network for training, and the structure of the corresponding deep learning network modified.

This paper includes three main contributions. Firstly, in the process of preprocessing, the author uses the short-time Fourier algorithm (STFT) to extract the time-frequency information of the signal, which can more characterize different RF signals. Secondly, in order to improve the operation efficiency, the author resamples the signal, which cannot weaken the ability to represent the signal. Thirdly, a deep learning algorithm based on Long Short-Term Memory (LSTM) is proposed. The algorithm has a better classification effect on the input time-frequency sequence extracted from the time-frequency graph, so as to identify the type and flight state of the UAV more accurately.

2 LITERATURE REVIEW

To detect UAV more effectively, MHD Saria Allahham et al. proposed an one-dimensional multi-channel convolution neural network method for UAV detection, type recognition and state recognition based on deep learning. It can better represent the new features in the dataset in a more compact form [3]. Wang et al. proposed an

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anomaly detection method for UAV system based on Long Short-Term Memory. They compared the predicted value with the uncertain interval to achieve anomaly detection [4]. Medaiyese et al. proposed a UAV identification and classification algorithm based on pre-trained convolution neural network algorithm SqueezeNet [9]. Lai et al. proposed distance estimation based on deep learning [5]. The target detection method they used is based on You Only Look Once target detector. In this method, depth neural network and convolution neural network are applied to moving target distance estimation, and their performance in moving target distance estimation is tested. Additionally, to solve the problem of original feature deviation caused by dynamic flight features, Zhao et al. proposed a small UAV m-DS recognition algorithm based on dynamic feature enhancement [7]. Dynamic attribute guidance is used to enhance the (DAGA) algorithm to expand the feature domain for model training in order to achieve efficient multi-class recognition model in complex environment. I Nemer et al. used ensemble learning based on hierarchical concept to classify the types and flight states of UAV [2]. The method consists of four classifiers, which work in a hierarchical way to detect and classify different information of UAV. What is more, Knoedler et al. proposed an approach of Track-before-Detect applies unthresholded measurements to overcome these situations that it is difficult to detect and track small UAV in GSM passive radar [6]. In addition, in the natural environment, signal interference is inevitable. Ezuma et al. used multistage detector to distinguish signals emitted by UAV controllers from background noise and interference signals [8]. Their method solved the problem of using passive RF monitoring system to detect and classify UAV in the presence of wireless interference signals.

However, there are some challenges for researchers. The accuracy of detecting unknown UAV still needs to be improved. The accuracy of detecting unknown UAV still needs to be improved. If a new type of UAV invades, few systems can detect the unmanned flight status of the more effectively, to determine the intention of the UAV. What is more, how to greatly reduce the cost of UAV detection system is also one of the current problems, when dealing with the complex natural environment and the accuracy does not decline. This requires not only the improvement of software and algorithms, but also the progress of hardware technology.

In the following parts, the mathematical model and related theories of the system are given. Next, the UAV signal classification algorithm, based on deep learning, is introduced. Finally, the simulation results are illustrated and the conclusion is proposed.

3 THEORETICAL BASIS AND DATASET

In this part, a brief introduction is given to the basic concepts that are used, including STFT and LSTM.

3.1 STFT time and frequency domain variation

In this paper, the author demodulates the ADC data of 2.4G band signals in various UAV control paths provided in the study of Al-Sa'D et al. [1]. Since it mainly depends on the communication logic controlled by different UAV (with different packet length, packet interval, packet frequency) for classification, it is necessary to STFT transform the above ADC data x (t) to convert the time domain signal into the time frequency domain signal, as shown in the following formula 1. In the formula, T represents the sampling period of STFT.

$$X(t,f)=\int_{t-\frac{T}{2}}^{t+\frac{T}{2}} x(t_0)\cdot e^{j2\pi f t_0}\,dt_0 \tag{1}$$

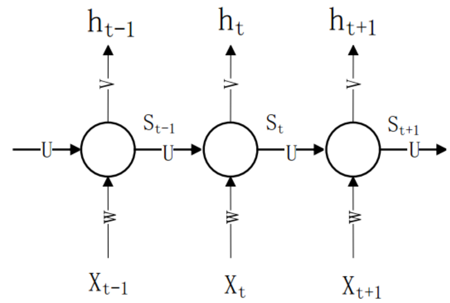

Figure 1: RNN structure diagram

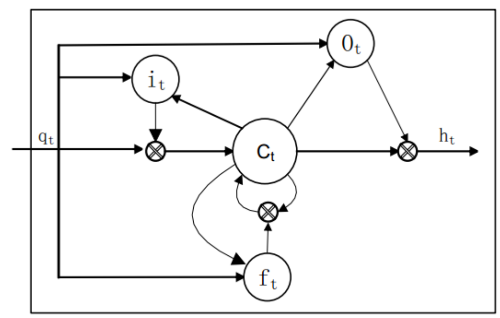

Figure 2: LSTM unit composition structure diagram

3.2 LSTM Deep Learning Network

The communication law of UAV is used to distinguish its types, convert the time domain data of ADC into time-frequency signal sequences. And then author extracts the features contained in time domain and frequency domain in the communication process of UAV. Lastly, LSTM deep learning network is selected as classification network.

Long Short-Term Memory (LSTM) is a kind of time cyclic neural network, which is specially designed to solve the long-term dependence problem of general RNN (cyclic neural network), and all RNN have a chain form of repetitive neural network modules. The idea of RNN is to use temporal information to model explicitly, and its network structure is shown in figure 1

RNN has shown great performance to solve NLP issues. However, compared to RNN, LSTM can learn to rely on information for a long time, being able to capture validity characteristics with much longer time than RNN, and its structure is shown in figure 2

Figure 2 is the basic component of LSMT-memory unit, which includes information Ct that can control memory. The control gates are input gate it, output gate Ot and forgetting gate ft. The memory

Table 1: Deep Learning Network parameters based on LSTM

Serial number	Layer type	Parameters
1	Sequence Input Layer	k*n
2	Bi-LSTM Layer	128
3	Fully Connected Layer	16
4	Bi-LSTM Layer	32
5	Fully Connected Layer	4/9
6	Softmax	\
7	Classification Layer	\

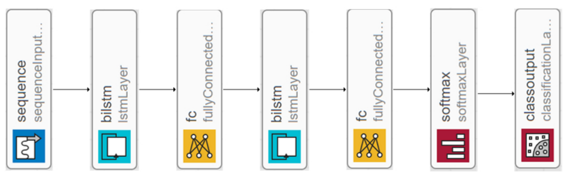

Figure 3: Deep Learning Network structure diagram based on LSTM

unit can decide which information to save or delete. Taking the previous state ht-1 and Xt as input, the t-moment output is determined by both the input and the output St-1 of (t-1)-moment. According to a large number of NLP data tests, memory units are effective in capturing long-term dependency information. This section mainly introduces the STFT algorithm for transformation of time and frequency domains and LSTM deep learning network. Next, the UAV signal classification algorithm based on deep learning, which is designed by the author, will be introduced.

4 IMPROVED UAV SIGNAL CLASSIFICATION ALGORITHM BASED ON DEEP LEARNING

This section will mainly introduce the UAV signal classification algorithm based on deep learning, and it can be divided into two parts, which are preprocessing and deep learning training.

The preprocessing part mainly contains two steps. First step is the time-frequency domain information X(t, f) of the signal extracted from the STFT transformation that is mentioned in the previous section. The second step is to reduce the noise of the time-frequency domain information X(t, f), and then carry out frequency filtering and time-domain filtering, as shown in the following formula 2.

$$X_2(t, f) = \int_{f-\frac{M}{2}}^{f+\frac{M}{2}} \int_{t-\frac{T}{2}}^{t+\frac{T}{2}} |X(t_0, f_0)|\, dt_0 df_0 \tag{2}$$

Finally, X2(t, f) is down sampled and converted into a sequence, which is represented as follows.

$$\begin{aligned} Y = [&X_2(t_0, f_0), X_2(t_0, f_1), ..., X_2(t_0, f_n), \\ &X_2(t_1, f_0), X_2(t_1, f_1), ..., X_2(t_k, f_n)] \end{aligned} \tag{3}$$

Next, the author needs to use deep learning network for classification. In this paper, a deep learning network based on LTSM is designed for the above data classification problems, and its network structure is shown in figure 3.

As can be seen from the above figure, the network has a total of seven layers. It mainly includes five components. Firstly, in Sequence Input Layer, the network input is a sequence of time-frequency domain signals, and the sequence length is kn. Secondly, Bi-LSTM Layer is the basic unit of LSTM network. Thirdly, in the Fully Connected Layer, each node of the full connection layer is connected to all the nodes of the upper layer, which is used to synthesize the previously extracted features. Fourthly, Softmax model belongs to the multi-classification regression model, which is based on logistic. Lastly, it is the Classification Layer. The parameters of each layer of the network are shown in table 1

5 RESULTS AND DISCUSSION

To verify the performance of the above algorithms, the corresponding experimental platform is built below. In addition, the provided UAV communication data are brought into the experimental platform for training and testing. As there are communication data of nine different flight attitudes of four kinds of UAVs, including AR drone, Background Ra, Bepop drone, Phantom drone UAV, the simulation tests of UAV recognition and UAV flight state recognition are carried out in this paper.

The first is the UAV type recognition simulation experiment, and the convergence of the training results are shown in figure 4. What is more, the effect of data classification is shown in figure 5

As can be seen from figures 4 and 5, the deep learning network designed in this paper can effectively extract signal features from the training data, and the training data part does not misjudge the type of UAV. It can also be seen that with the increase of the number of iterations, the classification accuracy increases and the loss decreases. When the number of iterations increases to 100, the classification accuracy and loss tend to be stable. At the same time, it also shows that it is enough to carry out 200 iterations, and the experimental results are convincing. In order to further verify the reliability of the algorithm, the original data is randomly divided into training data and test data (80% of training data). By training and prediction classification repeatedly, the average is obtained, and the classification result is shown in figure 6

From the above figure, this algorithm has good classification performance. The recognition rates of the three drones of AR drone, Background Ra, Phantom drone are all above 98%. What is more, Bepop drone is slightly weaker at 82%, and there is a chance of 17% being misjudged as AR drone. The reason is that Bepop drone and

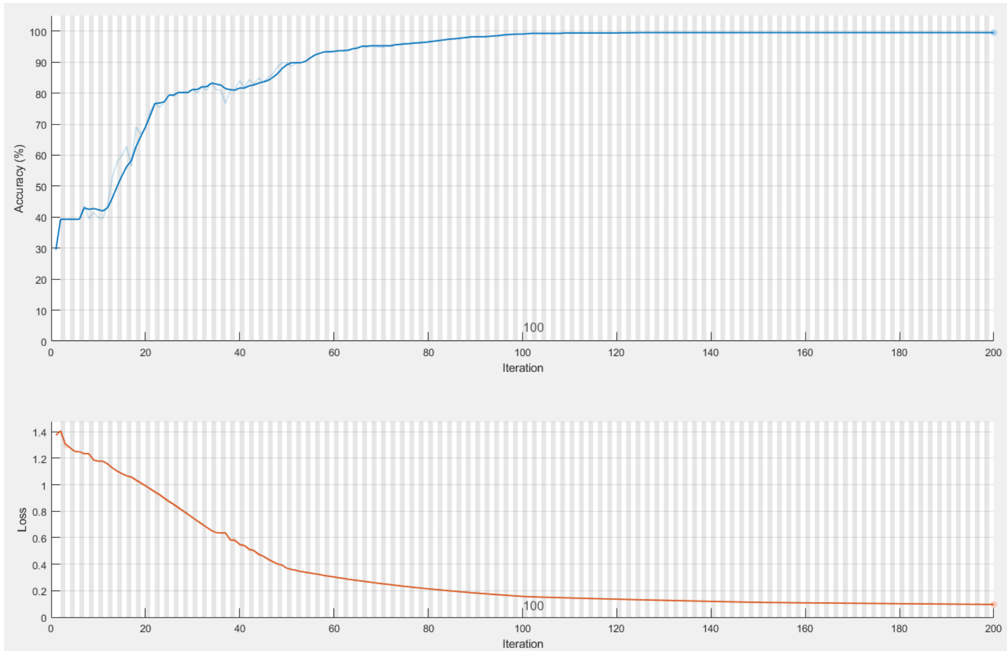

Figure 4: The training effect varies with the number of iterations

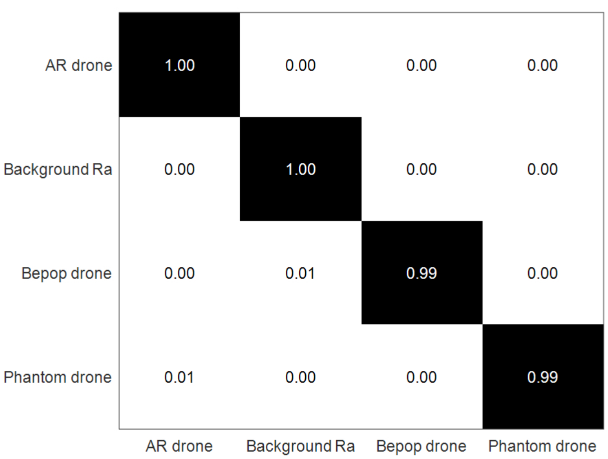

Figure 5: Confusion Matrix of UAV Type Classification

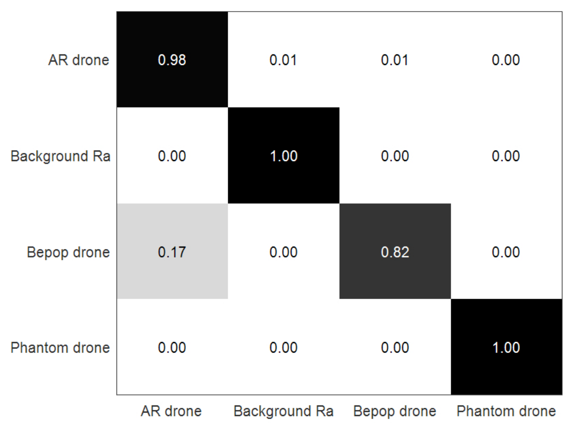

Figure 6: Classification effect diagram

AR drone are made by the same company, and the RF signals they use for communication have similar features. All of the information above proved that the algorithm proposed in this paper can effectively identify the type of UAV.

The next step is to test the deep learning algorithm to identify the attitudes of nine different drones, which can help the system to better determine the flight intention of the UAV, to determine the next step of operation, like attack, ignore, or warning. The convergence of the training results is shown in figure 7, and the effect of data classification is shown in figure 8

From figures 8 and 9, it can be known that the deep learning network, which is designed in this paper, basically does not misjudge the attitude recognition of UAV in the part of training data. The average classification accuracy is up to 0.99, the variance less than 0.001, which means the algorithm this algorithm can classify all 9 flight states of UAV accurately. Figure 7 is the same as figure 4, when the number of iterations reaches 100, the classification accuracy and loss of the algorithm tend to be stable. This shows that the algorithm proposed in this paper has a fast convergence speed and is feasible in concrete application, whether it is to detect the category of UAV or the flight state of UAV. Similarly, to further

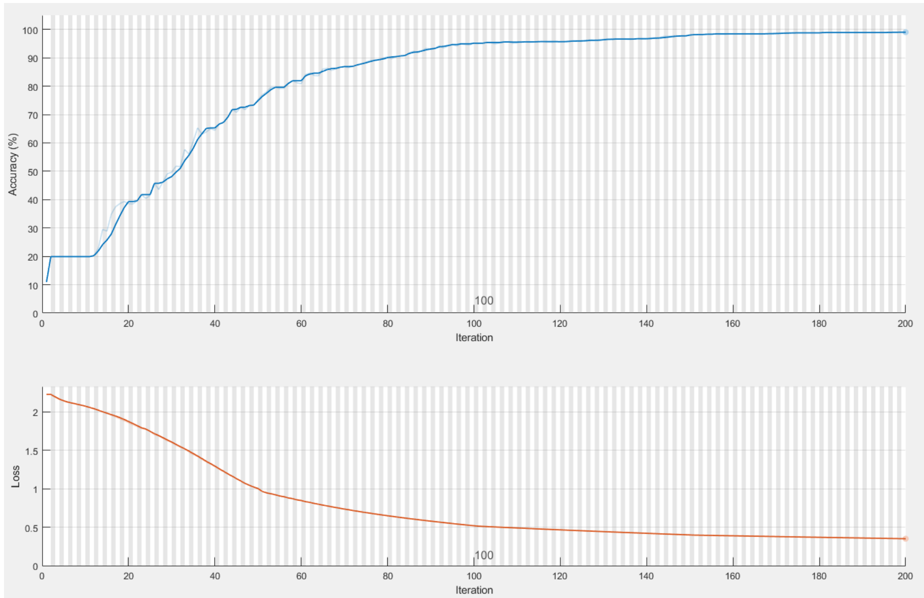

Figure 7: The training effect varies with the numbers of iterations

	0	16	18	19	20	21	22	23	24
0	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
16	0.04	0.95	0.01	0.00	0.00	0.00	0.00	0.00	0.00
18	0.00	0.01	0.99	0.00	0.00	0.00	0.00	0.00	0.00
19	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
20	0.00	0.00	0.00	0.02	0.98	0.00	0.00	0.00	0.00
21	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
22	0.00	0.00	0.00	0.00	0.00	0.01	0.99	0.00	0.00
23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00
24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00

Figure 8: Confusion Matrix for status Classification of UAV

verify the reliability of the algorithm designed in this paper, the original data are randomly divided into training data and test data (80% of training data). Additionally, the training and prediction classification are carried out in turn, and after repeating several times, the average can be gained. It can be inferred that although the attitude recognition effect of this algorithm is slightly worse than that of UAV, the accuracy is still improved.

Besides, there is no doubt that with the gradual popularity of UAV, the detection and identification methods of UAV are bound to develop gradually. Both the identification of the types of UAV and the detection of the flight status of UAV will be gradually diversified and many new methods will be proposed. These methods may not only use traditional features to detect, such as RF signals and image monitoring, but also integrate multi-angle and more comprehensive features for UAV detection.

6 CONCLUSION

In view of the increasing demand for passive detection of UAV, a UAV classification algorithm based on deep learning, by using radio communication information of UAV, is proposed in this paper. And a corresponding experimental platform is built to verify the effectiveness and reliability of the scheme. The experimental results show that based on the algorithm, the average recognition rate for identifying types of UAVs in the test data is 95%, and the recognition rate of most types of UAVs is more than 98%. In addition, the classification rate for the flight attitudes of UAVs can reach more than 95%. It indicates that the classification algorithm, which is designed by the author, can effectively meet the needs of UAV detection and recognition in the actual scene. What is more, there are still some challenges in the current research, and the classification accuracy of Bepop drone still needs to be improved, as Bepop drone and AR drone are made by the same company, and the two unmanned machines are similar to each other. For the following work, the author will continue to optimize the classification algorithm. Moreover, in order to improve the classification accuracy of Bepopdrone, the author will mine the deep features of the data to train the network in the future.

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