Digital Signal Modulation Classification using Data Conversion Method based on Convolutional Neural Network

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Abstract. Automated modulation classification (AMC) plays a very important part in cognitive electronic warfare. Deep learning (DL) is a new machine learning (ML) method, which has been successfully implemented in many application fields. This paper proposes a new data conversion algorithm in order to gain a better classification accuracy of target signal modulation. Then a Convolutional Neural Network (CNN) architecture is developed, and its performance is proved to be better than the traditional data conversion method. In addition, the impacts of representation on classification performance are also analysed. Experimental results demonstrate the significant performance advantage of the proposed data conversion method using DL-based approach for modulation classification.

1. Introduction

In order to meet the challenges of the increasingly complex battlefield electromagnetic environment, cognitive electronic warfare attracts extensive attention as a new idea and new mode of electronic warfare [1]. The idea of cognition was first manifested in the field of cognitive radio. Its core technology is the ability to perceive the surrounding environment. In order to complete cognitive target reconnaissance and subsequent intelligent interference, the key task is to identify the modulation type of the target signal.

The automatic modulation classification (AMC) of target signals has been booming since the 1970s [2]. In general, the existing algorithms to solve the modulation recognition problem can be divided into two categories, namely likelihood-based (LB) recognition algorithms [3-6] and feature-based (FB) recognition algorithms [7-10], both algorithms have flaws. LB algorithm can obtain satisfactory performance, however, it has not been widely used due to its high computational complexity. In FB recognition algorithms, the most important part of the FB recognition algorithm is to find features that reflect the modulation characteristics of the received signal, such as high-order cumulants, related parameters, and envelope spectrum. However, the above features are all made by hand and not intelligently mined, and these methods need to extract and fuse multiple features of the signal. In addition, FB algorithm is difficult to achieve the expected results under low signal-to-noise ratio (SNR). These reasons inspired the search for a simpler modulation recognition method.

The development of deep learning (DL) in many fields has shown great potential and strength, which prompting us to apply DL to modulation recognition. In essence, modulation recognition is also a pattern
recognition. The purpose of this study is to apply DL to the field of AMC, and extract deeper and richer features through DL to identify modulation types. There have been many works, the instantaneous features of the signal to be identified are extracted in [11], and then the corresponding neural network is designed to identify several modulation methods. In [12], Support Vector Machine (SVM) is used to classify the extracted features, but the range of SNR is relatively limited. In [13], a convolutional neural network (CNN) is used to identify the constellation of the signal, but the network structure is too complicated and the performance is poor at low SNR. The constellation image feature recognition method based on DL technology has become a popular modulation pattern recognition method [14], [15]. Paper [16] transformed the modulated signals into constellation diagrams, which provides a certain idea. The principle of this method is to use the characteristic constellation images corresponding to different digital amplitude and phase modulation signals to be unique, thereby classify the modulation type of the signal.

This paper proposes a method for converting target signals into constellation diagrams. The difference between this method and directly mapping signals into constellation diagrams is that it uses the density information of constellation points and uses distinguishing color processing for areas with different densities. With the help of the CNN model in DL, the three-channel constellation in different modulation modes can be fully used. Experiments prove that this method effectively improves the classification accuracy compared with traditional methods. In addition, we also explored the effect of using different window statistical densities and choosing different color on the experimental results.

Fig. 1 demonstrates the overall process of modulation classification using two data conversion methods. In the first method, the received target signal is directly mapped into the constellation diagram, and then gray image is obtained for classification. In the second method, density of the signal points is accounted, and the density information is used to obtain a three-channel image.

![Two data conversion methods](image)

The organizational structure of this paper is as follows. We first give an overview of the signal format and develop two data conversion methods in detail. We then briefly introduce the basic theory of CNN. Finally, some parameter settings and experimental results of training on the generated data set are given to demonstrate the performance advantage of this paper.

### 2. Data Conversion method

Commonly used digital modulation schemes include amplitude shift keying (ASK), frequency shift keying (FSK) and phase shift keying (PSK). In addition, there are mixed modulation methods such as quadrature amplitude modulation (QAM) [17-18]. In order to make better use of CNN classification, we have to convert the target signal into a constellation diagram. The general form of the complex envelope of the baseband signal is:

\[ r(t) = s(t; u_i) + n(t), \]

where

\[ s(t; u_i) = a_i \sum_{k=1}^{K} s_{k}^{(i)} g(t - (k - 1)T), 0 \leq t \leq KT \]

is the noise-free baseband complex envelope of the received signal, \( n(t) \) is the real-time noise at time \( t \). In Equation (2), \( a_i \) is the signal amplitude, \( \{s_k^{(i)}, 1 \leq k \leq K\} \) denotes \( K \) complex symbols taken from the \( i^{th} \) modulation format, \( T \) is the signal period, \( g(t) \) is the impulse response filter.
\( u_i = \{ a_i, g(t), \{ s_k^{(i)} \}_{k=1}^K \} \) is the multi-dimensional vector containing the \( i^{th} \) modulation type of the received signal. The goal of modulation classification is to identify the category \( i \) from the received target signal \( r(t) \).

Fig. 2 shows the target signal received directly from the communication system. In order to obtain the constellation, the real and imaginary parts are converted to the complex plane, the modulated signal will show an aggregated characteristic in the coordinate plane, and its shape is similar to a constellation, so this diagram is called a constellation diagram. Use constellation to classification can successfully transform modulation recognition problems into pattern recognition problems.

Some constellations diagrams of different modulation categories are shown in Fig. 3. In the constellation plane, the distance between the constellation point and the origin represents the amplitude of the signal, and the angle between the constellation point and the positive direction of the horizontal axis represents the phase. When a signal is received, it is easy to map the discrete signal points to the constellation diagram.

Although feeding the constellation diagram into CNN can already get a good classification accuracy, this only uses the information of one channel, and CNN can be used to process three-channel image, so data conversion methods such as direct mapping does not fully utilize the capabilities of the model. In order to make full use of the information of the received signal and the potential of CNN, we propose a new data conversion method, which can express the density information of the constellation points in chromaticity to generate a three-channel diagram. The main idea of this method is to count the density
around each point within a certain size window before mapping the data into constellation points, and use different color to distinguish density characteristics.

Fig. 4 presents the process of this method. The basic idea is that the projection points of the signal points contaminated by noise in the two-dimensional complex plane will deviate from the ideal point. Therefore, the density of points in different regions of the complex plane is different. Use an appropriately sized density window to calculate the point density of different areas in the complex plane, so that the difference in density can be converted into color to obtain a three-channel image. The following will introduce how to use MATLAB software tools to process the signal in detail to obtain a three-channel image.

![Fig. 4 Process of data conversion method](image)

(1) Map the received target signal to the complex plane to get the gray image. Let \( P(x,y) \) denote the pixel value in the gray image, and \( P(x,y) = 0 \) if there is no constellation point projected at \((x, y)\).

(2) Determine the range of sample points in the constellation diagram. Choose the size of the density window according to the range of sample points. The window size is determined by

\[
s = \frac{x_{end} - x_{start}}{M}
\]  

Here, \( x_{start} \) and \( x_{end} \) are the coordinates of two points located at the boundary of one constellation, and \( M \) represents the number of division parts of the constellation area. We generally set \( M = 30 \). Let \( dots(x, y) \) denote the existence of the constellation points, we set

\[
dots(x, y) = \begin{cases} 
1 & \text{otherwise} \\
0 & p(x,y) = 0 
\end{cases}
\]  

(4)

Then count the number of points in the density window around each point, the density at point \((x_i, y_i)\) can be represented as

\[
\rho(x_i, y_i) = \frac{\sum_{x=x_i-s}^{x_i+s} \sum_{y=y_i-s}^{y_i+s} dots(x, y)}{(2s)^2}
\]

(5)
(3) Normalize the density of constellation points in each area and map the normalized density to a color bar. Assume $\rho_{\text{max}}$ and $\rho_{\text{min}}$ represent the maximum and minimum density, respectively. $\lfloor \cdot \rfloor$ represents the floor operator, $K$ is the total level of color in the color bar, and we set $K = 64$. Then the order of selected color at point $(x_i, y_j)$ can be obtained by

$$k(x_i, y_j) = \left\lfloor \frac{\rho(x_i, y_j) - \rho_{\text{min}}}{\rho_{\text{max}} - \rho_{\text{min}}} \right\rfloor \times K$$  \hspace{1cm} (6)$$

According to the density value of the constellation points in each small area on the constellation diagram, the color on the color bar is correspondingly taken, and the constellation points in the small area are set as the corresponding color.

According to this data conversion method, as shown in Fig. 5, we can obtain some three-channel constellation diagrams of various modulation types at SNR=6dB. Compared with Fig. 3, the constellation point's concentration characteristic is more obvious, which is obviously more conducive to classify.

![Constellation Diagrams](image)

**Fig. 5 Three-channel constellation diagrams with different modulation methods at SNR=6dB**

### 3. Convolutional Neural Network

Artificial neural networks (ANN) have been the focus of attention in recent years. With the rise of artificial intelligence, ANN have also begun to be widely studied. In this paper, the common CNN will be used to modulate and identify the constellation. CNN is a feedforward neural network that contains convolution calculation and has a deep structure. It is one of the representative networks of deep learning [19]. Since the CNN can perform translation-invariant classification, it is also called "translation-invariant neural network" [20].

CNN contain multiple layers of neural networks, the main structure of which is a convolutional layer, a pooling layer, and a fully-connected layer. Through the connection and reasonable design of the convolutional layer and the pooling layer, the salient features of the image can be reasonably extracted, and finally the connection output recognition is performed through the fully-connected layer, so as to achieve the purpose of image recognition. Fig 6 is an example of convolutional neural feature extraction.

In general, the basic structure of the CNN model includes the following parts:

- **Input layer**: Input the original data to the neural network model through this layer for model training. If the layer input is a picture, then the actual input to the neural network is not a picture, but the picture pixel value.

- **Convolutional layer**: The convolutional layer can be used to extract a part of the features of the input object. The feature extraction of the input is achieved through the convolution kernel. Because one convolution kernel can only extract part of the input features, in order to get more features of the input, it is necessary to set up multiple different convolution kernels, so that the input features can be fully extracted. Of course, the size and number of cores can be selected according to actual needs.
Pooling layer: It can also be called a down-sampling layer. The pooling layer can reduce the dimension of the input feature map, perform the necessary compression processing on the data volume, and can reduce the number of parameters. The fitting phenomenon occurs, and the fault tolerance of the model can be improved to a certain extent. There are many forms of pooling, and the most commonly used ones are uniform pooling and maximum pooling.

Fully-connected layer: Fully connected is a one-dimensional vector obtained by weighted summation of all weighted inputs and fully connected inputs, and then outputs various classification situations through probability values.

Output layer: The output layer is generally an SVM or softmax classifier, which is used to classify and output the recognition results. The number of nodes in this layer is equal to the number of classified categories.

Fig. 6 The basic structure of CNN

4. Experiment and Results
In this section, simulations are carried out to verify our conversion approach. We first introduce the dataset used in experiment and give some parameters. Then, simulation results are presented to validate the accuracy of classification.

4.1. DataSet and parameters
In this paper, seven common signal modulation schemes are mainly identified, including BPSK, QPSK, 8PSK, 8QAM, 16QAM, 32QAM and 64QAM. Datasets in experiment are generated from the two data conversion methods. The SNR range is from -6dB to 14dB with a step size of 2. The first one contains the constellation maps directly mapped by these 7 types of modulated signals and each type of modulation contains 1100 pictures. The second data set is similar to the first data set and also contains 7700 pictures. 80% images of the data set are selected for training, and the remaining 20% for testing.

In addition, we use a four-layer CNN model and the hyperparameters used at the beginning are shown in Table 1.

Table 1 The initial configuration of hyperparameters

| Hyperparameters | Weights |
|-----------------|---------|
| Learning Rate   | 0.01    |
| Hidden layers   | 6       |
| Iteration       | 100     |
| Batch size      | 64      |

4.2. Impact of two data conversion method
First, we use the CNN4 structure to train and test the two data sets separately, and obtained the classification accuracy of the two data conversion methods at -6dB to 14dB. Fig. 7 shows the overall accuracy versus SNR results. In the range of low SNR, the classification accuracy of image using density information has been greatly improved. At high SNR, both data conversion methods exhibit high classification accuracy.
Fig. 7 Accuracy vs SNR for CNN4

Fig. 8 demonstrates that the three-channel constellation using density information also has better classification accuracy at mixed SNR conditions. As shown in those two figures, using gray image classification can finally achieve a test accuracy of 76%, which is is 12% lower than using color images. At the same time, in order to make the result more intuitive, the confusion matrix classified by the two data conversion methods at mixed SNR is given in Fig 9. The classification results of the two methods are roughly similar, 16QAM, 32QAM and 64QAM will have a small number of errors, BPSK, 8QAM, 8PSK and QPSK can be correctly classified.
4.3. Impact of density window size

Since the size of the density window used to generate the color constellation image will have an impact on the classification accuracy, we further extend the proposed data conversion method. The selected area should be neither too small nor too large, the selection of the density window should be based on the range of the constellation points. The method we use is to select the range by different equal divisions. We conducted experiments on different divisions of the complex plane by changing the value of M. Different sizes, including M=10, M=30, M=50, and M=70, are considered. Fig.10 plots the test accuracy of each method of dividing density windows under three SNR scenarios. It can be seen that the best results are achieved at 30 equal divisions under each SNR.

4.4. Impact of different color

In addition to the size of the selected area, the color chosen for different densities is another key parameter of the constellation diagram. Table. 2 demonstrates the first eight levels of RGB values in every selected color schemes. K=64, we denote $k(i)$ as the $i^{th}$ color in the color bar, here, we only give the first eight levels digits. Through the above RGB chroma settings, color image can be obtained as shown in Fig. 11.
Table 2: RGB chroma value selection

| i | R   | G   | B   |
|---|-----|-----|-----|
| 1 | 0.0417 | 0.0000 | 0.0000 |
| 2 | 0.0833 | 0.0000 | 0.0000 |
| 3 | 0.1250 | 0.0000 | 0.0000 |
| 4 | 0.667  | 0.0000 | 0.0000 |
| 5 | 0.2083 | 0.0000 | 0.0000 |
| 6 | 0.2500 | 0.0000 | 0.0000 |
| 7 | 0.2917 | 0.0000 | 0.0000 |
| 8 | 0.3333 | 0.0000 | 0.0000 |

**Hot**

| i | R     | G   | B   |
|---|-------|-----|-----|
| 1 | 1.0000 | 0.0000 | 0.0000 |
| 2 | 1.0000 | 0.0159 | 0.0000 |
| 3 | 1.0000 | 0.0317 | 0.0000 |
| 4 | 1.0000 | 0.0476 | 0.0000 |
| 5 | 1.0000 | 0.0635 | 0.0000 |
| 6 | 1.0000 | 0.0794 | 0.0000 |
| 7 | 1.0000 | 0.0952 | 0.0000 |
| 8 | 1.0000 | 0.1111 | 0.0000 |

**Autumn**

| i | R     | G   | B   |
|---|-------|-----|-----|
| 1 | 0.0000 | 0.5000 | 0.4000 |
| 2 | 0.0159 | 0.5079 | 0.4000 |
| 3 | 0.0317 | 0.5159 | 0.4000 |
| 4 | 0.0476 | 0.5238 | 0.4000 |
| 5 | 0.0635 | 0.5317 | 0.4000 |
| 6 | 0.0794 | 0.5397 | 0.4000 |
| 7 | 0.0952 | 0.5476 | 0.4000 |
| 8 | 0.1111 | 0.5556 | 0.4000 |

**Summer**

| i | R     | G   | B   |
|---|-------|-----|-----|
| 1 | 0.0000 | 0.0159 | 0.9921 |
| 2 | 0.0000 | 0.0317 | 0.9841 |
| 3 | 0.0000 | 0.0476 | 0.9762 |
| 4 | 0.0000 | 0.0635 | 0.9683 |
| 5 | 0.0000 | 0.0794 | 0.9603 |
| 6 | 0.0000 | 0.0952 | 0.9524 |
| 7 | 0.0000 | 0.1111 | 0.9444 |
| 8 | 0.0000 | 0.127 | 0.9365 |

**Winter**

Fig. 11 BPSK signals with different color schemes at SNR=2dB

Fig. 12 shows the effect of selecting different colors on the classification accuracy. In the case of SNR = -2dB, 4dB and 2 dB, the four color processing methods are considered, namely ‘Hot’, ‘autumn’, ‘summer’ and ‘winter’. As shown in the figure, the use of strongly contrasting colors can lead to better
classification accuracy. This phenomenon can be explained as follows. If the color contrast of the graph is strong, the areas with higher density will be more prominent. Obviously, in our experiment, the best coloring method is ‘hot’, which can achieve 91.4% accuracy at -2dB.

5. Conclusion
This paper studies the CNN model and its application in modulation classification. Two data conversion methods are introduced to generate gray images and three-channel images, respectively. At the same time, for the data conversion method of generating color images, we further explored the details of its application, such as the selected window and color. Compared with the traditional modulation classification algorithm, our data conversion method based on CNN avoids manual feature selection and provides excellent classification accuracy.

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