Efficient Modulation Classification Based on Complementary Folding Algorithm in UVLC System

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Abstract—Modulation classification (MC) has become a widely used technology, which is of great value in both commercial and civil applications. It actually completes the classification task of modulation signal through various means. In recent years, modulation format recognition based on deep learning (DL) has achieved great success. However, in practical application, the computational cost and model complexity have become the biggest obstacles of the traditional MC based on DL. To solve this problem, we propose complementary folding algorithm (CFA). This is an algorithm based on classical modulation classification (CMC), which folds and splices the features of the input neural network (NN), so that these features have both large-scale and small-scale dual branch receptive fields. The research results prove that under the same network structure and data quantity, both the correctness rate and the convergence speed of CFA are significantly improved in the communication experiment based on underwater visible light communication (UVLC). It is also worth mentioning that because of the particularity and complexity of the channel, UVLC system can be divided into different regions. In any region, CFA performs better than CMC, so we can prove that this algorithm also has excellent robustness.

Index Terms—Classical modulation classification (CMC), complementary folding algorithm (CFA), neural network (NN), Underwater visible light communication (UVLC).

I. INTRODUCTION

Underwater visible light communication (UVLC) is a kind of amplitude modulation realized by LED. It can realize the high-speed transmission of information through the change of the intensity of visible light emitted by LED [1]. It is a promising communication technology in the future. In the foreseeable future, UVLC will develop towards flexible communication (FC). It will be able to flexibly allocate resources dynamically to improve spectrum utilization and meet the needs of various frequency bands. And one of the most important key technologies of FC is Modulation classification (MC). It is a widely used technology in the field of communication, which can automatically learn and adjust. When the transmitter adjusts the transmission format due to external factors, MC can help the receiver also automatically identify and adjust the demodulation mode [2]. Therefore, real-time is an important requirement of MC. The research in this paper mainly focuses on the modulation classification (MC) based on feature extraction without any prior information. With the development of deep learning, neural networks (NN) is undoubtedly one of the best choices for MC tasks. Features with different modulation formats are often nonlinear, while NN has strong nonlinear modeling ability [3]. Therefore, classical modulation classification (CMC) splits the modulation signal into in-phase and quadrature component (IQ) samples and sends them to NN with relatively simple structure. Through the nonlinear modeling of NN, we can quickly get relatively high discrimination accuracy [4]–[6].

However, in many applications of UVLC, there is often no huge amount of data for training. And UVLC channel is more complex than the general situation, it also has its unique nonlinearity. In addition, the computational power of simple NN is limited. If the amount of data is not large enough, the discrimination ability of NN will be limited in the face of modulation formats with high complexity and high similarity [7]–[9]. Practical experiments show that in the face of the above situation, the classical modulation classification (CMC) is often difficult to trade off between accuracy and computational overhead [10]. This is also a major challenge when MC is applied in UVLC [11].

Therefore, in order to solve the above problems, this paper proposes complementary folding algorithm (CFA) based on CMC. The algorithm obtains the receptive field in a large range and a small range through folding of different orders, and then selects different branches to rely on, so that the input data has the overall and local characteristics at the same time. CFA can effectively solve the problem that it is difficult to balance the amount of data, accuracy and model complexity. It not only significantly improves the accuracy and convergence speed, but also does not increase the complexity of neural network. Through experiments in UVLC channels under different conditions, we verify the superior performance and robustness of CFA compared with CMC.
II. PRINCIPLE

In feature-based MC, the most classical way is to split the received signal into IQ samples. Consider a set of received complex valued baseband signals $y = [y(i)]_{i=1}^K$, CMC split the real part and the complex part of each $y(i)$ in this group of signals to obtain the IQ samples. It can be described as,

$$IQ = \left( \begin{array}{c} \text{imag} [y(i)] \\ \text{real} [y(i)] \end{array} \right)_{i=1}^K$$

(1)

The idea of CMC is to splice such two-dimensional data into $2 \times K$ dimensional data and send it to CNN network, or send the flattened $1 \times 2K$ dimensional data to DNN network. This method only works well in the face of OOK, 4PSK, 8PSK and 16QAM at high SNR. However, in the face of more complex modulation formats or more complex channels, the effect of CMC will decline sharply.

In view of this shortcoming of CMC, we propose a CFA algorithm. The key part of this algorithm is folding, which can localize and refine the receptive field of NN for constellation. In Fig. 1(a) and (b), we first select two modulation formats to show the folding process and polar angle histogram at each step, followed by the folding results of all modulation formats in Fig. 1(c). Where 2nd-folding indicates that the constellation is folded twice, and 4th-foldin indicates that the constellation is folded four times. They are the representatives of low-order and high-order folding, and they are also the two most important orders in CFA.

To verify that CFA outperforms CMC in more complex situations, we have selected two modulation formats based on probability shaping in addition to the above modulation formats: 8QAM-DIA and 8QAM-CIR show in Fig. 1(c). These two modulation schemes are proposed based on geometric shaping (GS), which optimizes the minimum Euclidean distance by redesigning the constellation point distribution. 8QAM-DIA is a diamond 8QAM composed of four constellation points in the inner ring and four constellation points in the outer ring. And 8QAM-CIR is a circular 8QAM formed by seven constellation points in the outer ring around the center. In addition, we also added 16APSK to the experimental group. It is a high-order modulation method often used in satellite channels. When visible light communication is applied to space scene, it is a frequently used modulation format. Obviously, the four modulation formats have high similarity and complexity in spatial distribution, which helps us fully compare the performance differences between CFA and CMC.

Folding is performed on IQ samples in CMC. First, we consider IQ samples as x-axis and y-axis data in Cartesian coordinate system, so that we can convert them into polar diameter components and polar angle components through coordinate axis transformation. After that, we fold the data based on the polar diameter component. The expression of folding function $\theta_{i}^{n}$ is shown as,

$$\theta_{i}^{n+1} = \theta_{i}^{n} - \sum \theta_{i}^{n}/length$$

(2)

where $\theta_{i}^{n}$ is the i-th data in the polar angle component of n-order folding, length is the amount of data for a set of polar angle components.

And while we stand in the perspective of Euler’s formula, the folding formula can also be expressed as,

$$Euler_{1} = A(\theta) e^{\frac{1}{2} j\theta}$$

$$\ldots$$

$$Euler_{n} = A(\theta) e^{\frac{n}{2} j\theta}$$

(3)

Where $Euler_{n}$ is the Euler formula form of polar angle component and polar diameter component after n-order folding. From the formula, we can see that folding is actually the square root of the polar angle component without changing the polar diameter component. A fold is completed by whitening the polar angle component once and taking the absolute value. For such a series of operations, we call it first-order folding. Theoretically, the order of folding can be accumulated indefinitely. However, this is meaningless, because the constellation will lose all features after too many folds. Our goal is to obtain local fine receptive fields.
Obviously, with each fold, our receptive field shrinks to half of its original size. After each folding, the distinguishing ability of the complex modulation format will be significantly improved. However, there is still a problem that high-order folding will lose some features. The characteristics of low-order modulation formats (such as OOK and 4QAM) will become very similar, which increases the difficulty for NN to distinguish them. On the contrary, the features extracted by low-order folding are not accurate enough to effectively distinguish high-order modulation formats in all cases. Therefore, on the basis of folding, we propose complementary folding algorithm (CFA) to solve this problem.

The idea of this algorithm is based on the fact that high-order folding is more sensitive to high-order modulation format and low-order folding is more sensitive to low-order modulation format. Therefore, we propose a two-branch structure, which selects the two orders that perform better in the low-order and high-order folding as branches, and splices them together. This has the advantage that NN can simultaneously extract features under large receptive fields and small receptive fields, and has the ability to distinguish all order modulation formats. We splice the 2nd-order and 4th-order folded data in a ratio of 1:1. In this way, we are equivalent to processing \(2 \times K\) dimensional data twice, and finally obtaining a group of \(2 \times 2K\) dimensional data. The flow of the whole algorithm is shown in Fig. 2.

**III. EXPERIMENTAL SETUP**

Our experiment is transmitted through QAM-CAP/APSK-CAP modulation in UVLC system. The sampling frequency of signal is 2.2 GHz. Firstly, we design the code table of six modulation formats, map the original data into the six modulation formats through the code table, and get the signal in the complex field. Among them, the number of subcarriers of each group of data is 1024, and 128 data are transmitted on each subcarrier, so each group of QAM/APSK data is 131072. After four times of up sampling and pulse shaping filter, the final amount of cap modulation data is 524288 for each group. The digital signal will
be converted into analog signal through DAC and transmitted through LED. Here we choose the blue chip (457 nm) of an RGBYC silicon substrate LED lamp. It’s studied by Nan Chang University [8]. Our signal will pass through the water tank and be received by the differential receiver. After equalization, CAP demodulation and LMS, we retrieve the signal in the complex domain and split it into IQ samples. In the experiment, LMS algorithm is used to solve the problem of ISI and linear distortion [12]. When we set the number of LMS filter taps to 13, the effect is the best. At this time, the ISI weight on the center tap is much higher than other taps. Therefore, it can be considered that the filter tap covers the length of ISI.

Because our experiment is carried out under the condition of UVLC, the unique nonlinearity of UVLC channel must also be taken into account. Due to the nonlinear electro-optic response of LED, the nonlinear amplification of electric amplifier and the square law detection of photodiode. When the $V_{pp}$ is too high, photodiode device enter the light saturation region, which will cause the unique nonlinearity of UVLC. The influence of nonlinearity is mainly manifested in that the constellation receiving the signal is no longer the standard lattice structure, and each constellation point outside is stretched to the center [13] and [14]. This is the reason why the SNR decreases after the $V_{pp}$ increases. Whether this nonlinearity will affect our algorithm is also one of the key points we should consider.

In the following experiments, we will first compare the convergence of the loss function when high-order and low-order folding algorithms train the modulation formats they are good at or not. This will prove that it is necessary for us to propose a dual branch structure according to their respective advantages and disadvantages. After that, we further prove this conclusion by comparing the performance of CMC, low-order folding, high-order folding and CFA in the training of all modulation formats. After that, we divide the experiment into weak nonlinearity and strong nonlinearity. By comparing the confusion matrix of each algorithm, we illustrate the advantages of CFA over other methods. Finally, by adjusting the LED voltage, we can control the received signal in the low signal-to-noise ratio region (insufficient voltage), the ideal region (appropriate voltage) and the nonlinear region (too high voltage). We will compare the training accuracy of CFA and CMC in all region to prove that it performs better in any case.

IV. EXPERIMENTAL RESULTS

In order to explore the advantages and disadvantages of high-order and low-order folding algorithms, we first study their training loss function. Because the receptive field of the low-order folding is not accurate enough, and the polar coordinate conversion may introduce additional complexity compared with the IQ samples of CMC, we think its ability to distinguish the high-order modulation of the constellation will be relatively poor. On the contrary, in the process of narrowing the receptive field, higher-order folding may lose some features, which may be fatal to the low-order modulation with simple features. With this conjecture, we divide the modulation formats used in the experiment into two groups: high-order and low-order. The second-order and fourth-order folding algorithms are used to train these two groups of modulation formats respectively. Fig. 4(a) shows the loss function during training. We choose cross entropy as the loss function of the model, which is a loss function suitable for classification problems. It can make up for the defects that the derivative form of sigmoid function is easy to be saturated and the learning rate decreases in the calculation of gradient descent.

Red line and black line in Fig. 4(a) are the performance of 2nd-folding and 4th-folding algorithms when dealing with the modulation format they are not good at (high to low, low to high). Because of their own defects, it can be seen that the training effect is very poor, and the jitter is large. They may be difficult to converge in the experiment. In the process of adjusting learning rate and other parameters, over fitting is very easy to occur. On the contrary, the effect of the green line and the blue line on the modulation format they are good at (high to high, low to low) is much better than the first two cases. It can be seen from the figure that when the second-order folding faces the low-order modulation format, it only takes three to four periods to quickly
reduce and converge the loss. While the fourth-order folding faces the high-order modulation format, even if the situation is more complex, it can also make the loss reach a lower level after more than ten periods.

Fig. 4(b) shows the performance of CMC, low-order folding, high-order folding and CFA in the face of all modulation formats. It is obvious from the figure that the convergence of the traditional method CMC (black line) is relatively stable, but the effect is general. After second-order and fourth-order folding (green line and blue line), the convergence speed is faster, and the test set loss can reach the level lower than CMC. However, they still contain the defects mentioned above. And it is worth noting that compared with the low-order folding algorithm, the loss caused by the high-order folding algorithm is smaller. This is because the high-order folding algorithm is only not good at facing the two low-order modulation formats of OOK and 4QAM, while it performs very well in the face of the remaining four high-order modulation formats. On the contrary, the low-order folding algorithm needs to face four modulation formats that it is difficult to distinguish. This can be seen more clearly in the confusion matrix below. Finally, the CFA method (red line) after the complementary combination of the two methods not only has fast convergence speed and low loss level, but also has strong robustness and can complete the convergence quickly.

Here, we divide the experiments into weak nonlinearity and strong nonlinearity. We first compare the confusion matrix under the condition of weak nonlinearity. Through the confusion matrix in Fig. 5(a) and (b), we can analyze whether various modulation formats can be correctly classified by NN, and if the classification is wrong, what kind of modulation formats will be wrongly classified. The above four confusion matrices are obtained on the UVLC system with $F_s = 2.2$ GHz, $I_{bias} = 150$ mA and $V_{pp} = 0.5$ V. At this time, the signal is located in the weak nonlinear region with high SNR. We compare the confusion matrix of CMC, second-order folding, fourth-order folding and CFA training all six modulation formats to further verify the conclusion explained by loss function in Fig. 4. From the confusion matrix, we can clearly see the difference between the four schemes.

The overall effect of CMC is general, and the ability to distinguish between high-order and low-order modulation formats is not outstanding. The distinguishing ability of second-order folding is very strong for low-order modulation format. It can be seen that there is no misjudgment between OOK and 4QAM in the confusion matrix. But when facing high-order modulation format, its distinguishing ability becomes very poor and unstable. In contrast, the fourth-order folding algorithm can be seen from the confusion matrix that it has sufficient distinguishing ability for high-order modulation format, but the effect will become very poor in the face of low-order modulation format. In the figure, the error rate of fourth-order folding for OOK is as high as 93.3%. Compared with other methods, the effect of double branch CFA is better than any other scheme, and the accuracy can easily reach more than 99%.

Fig. 6 shows the confusion matrix obtained by using four methods when $V_{pp} = 1.3$ V. In this case, the nonlinearity of the constellation of the received signal has been very obvious. From Fig. 6(a), we can see that CMC performs very poorly in the face of the nonlinearity of UVLC. In Fig. 6(b) and (c), We can see that the single high-order or low-order folding algorithm still has the same problem as in Fig. 5. In the face of the nonlinearity of UVLC, the effect of CFA is also reduced, but the effect is still the best of all methods.

It is worth mentioning that when the received signal enters the strong nonlinear region, 16QAM and 8QAM-CIR with similar constellation point distribution become more difficult to distinguish after SNR decreases. This can be reflected in the confusion matrix obtained by any scheme. Especially for the fourth-order folding, the features are lost more seriously after folding, and it is almost impossible to distinguish the two modulation formats.
This situation cannot be avoided even by CFA, but compared with the four confusion matrices in the figure above, we can clearly see that its ability to distinguish 16QAM and 8QAM-CIR is still the best. We can think that the effect of CFA is still much better than other schemes in the face of weak nonlinearity or strong nonlinearity.

By controlling the $V_{pp}$ between 0.1 V and 1.3 V, we can see the performance of CMC and CFA in all cases. As shown in Fig. 7, we adjusted the pin voltage of the LED to control the received signal in three different color regions (low SNR region, ideal region and nonlinear region). We compared the accuracy of final convergence after training through CMC and CFA. It can be seen that in the ideal area, the accuracy of CFA is more than 99%, which is much better than that of CMC. In the low SNR region and nonlinear region, the accuracy of CFA has decreased, but it is still much higher than CMC. It is also worth noting that when $V_{pp}$ exceeds 0.9 V, the accuracy of CFA does not decrease significantly while the nonlinearity of UVLC channel is gradually strengthened. This shows that it has a certain tolerance for the unique nonlinearity of UVLC. In all cases shown in the figure, the effect of CFA is much better than CMC, and does not increase the amount of data and model complexity. In the future, CFA may become a more efficient method to replace CMC.

V. CONCLUSION

Firstly, this paper proposes a folding method based on the traditional modulation format recognition method CMC, and the experiment is carried out in UVLC. The modulation signal IQ sample is transformed into polar coordinates and folded according to the polar angle component. Compared with CMC, the effect of folding is improved, but this algorithm has its own defects. The receptive field of low-order folding is not accurate enough, so the recognition accuracy of high-order modulation format is not high, while the receptive field of high-order folding is too small, ignoring the characteristics of low-order modulation format. Such reasons will lead to unstable training effect and difficult convergence. On this basis, we propose CFA. This method splices the results of high-order and low-order folding processing, so that the data has the characteristics of distinguishing high-order and low-order modulation formats at the same time, so that NN can achieve faster convergence and more accurate distinction. Experiments show that the accuracy of CFA can easily reach more than 99% in the region with weak nonlinearity, and its tolerance in other cases is also stronger than CMC and ordinary folding. In addition, CFA is also superior to other methods in terms of convergence speed. Its convergence can be completed in about 20 cycles without increasing the complexity of the model.

In the future, CFA still has room for continuous improvement and in-depth research. For example, the selection and splicing of complementary folding formats can be improved to make the distinguishable features of different modulation formats more obvious and the interference between them less. We can also optimize the structure of NN, or use equalization to deal with the nonlinearity of UVLC. In a word, there are still many improvements in this algorithm, which may be improved in robustness, accuracy, practicability, real-time and other aspects in the future, so as to meet the increasingly stringent challenges of transmission requirements in the communication era.

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