Modulation Classification based on Deep Learning for DMT Subcarriers in VLC System

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Abstract: We propose a deep learning(DL) enabled modulation classification scheme using only dozens of received symbols. For each DMT subcarrier in VLC system, experiments achieve 100% classification accuracy rate using 75 symbols received at BER threshold. **OCIS codes:** (060.2605) Free-space optical communication; (060.4080) Modulation;

1. Introduction

In recent years, visible light communication (VLC) based on light emitting diode (LED) has become a promising solution for future indoor wireless access [1-2]. Phosphorescent white LED is commonly used light source because of environment friend and low cost. However, typical VLC channel has limited bandwidth and uneven signal-to-noise ratio (SNR) over the operation bandwidth due to its poor frequency responses. Multiuser and channel overlap inevitably increase the electromagnetic complexity of VLC system. Many researches have been reported to cope with these problems, such as equalization and multi-band OFDM modulation [2-3]. In particular, Discrete Multi-Tone(DMT) with bit-loading technique is widely adopted. The modulation formats of subcarriers are dynamically adapted to serve multiuser and approach the channel capacity [3]. Modulation classification is important for dynamic allocation of DMT subcarriers, and it can also be used for spectrum management, signal confirmation and interference identification in optical wireless communications.

The conventional modulation classification technique can be classified into the maximum likelihood (ML) method and the feature-based classification method [4]. The ML method is based on the likelihood function of the received signal and it makes decision by comparing the likelihood ratio against a threshold, while the feature-based method employees several features and makes decision based on their observed values. Of the feature-based methods, the cumulants method [5] uses the cumulants and cyclic moments of the time domain signal waveforms to make classification, artificial neural network method [6] converts the constellation of modulated signals into images and feeds images into CNN for training and classification, it achieves better performance than the cumulants method. For most feature-based methods, sufficient samples reveal statistical features and improve the classification accuracy, but more data input increases the computation complexity and time delay, less data received at short intervals are preferred in the changing channel.

In this regard, we classify the modulation formats by pseudo constellation images which are generated with less received data. With N received symbols, we can get N(N-1) vectors between their constellation points, each vector corresponds to one pseudo symbol, then we have N(N-1) pseudo symbols to make one dense constellation image. Using images contain more constellation points, the CNN network can provide more accurate classification. In the simulation, the proposed scheme classified 6 modulation formats including BPSK,4-QAM,8-QAM,16-QAM,32-QAM and 64-QAM, and provides superior performance compared to the cumulants method. The scheme is also experimentally verified to classify the modulation formats of each DMT subcarrier in the fading VLC channel, the classification accuracy rate is 100% for 5 modulation formats using 75 symbols received at BER threshold.

2. Operation principle



Fig 1. (a) Converting constellation diagram into gray image. (b) Converting raw symbols into pseudo symbols (c) Images generated for six modulation formats at SNR=9dB.

To utilize the existing DL method, the complex data samples are firstly converted into images which can be handled by the CNN-based models. As is shown in Fig. 1(a), the symbol number within each pixel area is counted, and the constellation diagram on the complex plane is turned into a gray image. The gray image is handled with Gaussian filters using three different standard deviations, the generated images are used as three channel (red, green, and blue) data of a RGB image, which is used as inputs of CNN model.

The proposed scheme generate pseudo constellation images as is shown in Fig. 1(b): N received symbols are subtracted each other to construct N(N-1) vectors between different constellation points, each vector corresponding to a pseudo symbol, then the pseudo symbols are normalized and turned into image as depicted in Fig. 1(a). Fig. 1(c) shows the RGB images generated for six modulation formats at 9dB SNR. The images in the first and second row are generated with traditional method, using 1000 and 3000 raw symbols per image. The images in the third row are generated with proposed scheme, using 22350 pseudo constellation points made of 150 raw symbols. The pseudo constellation points made of QAM formats are rectangular lattice, and the Euclidean distance is reduced compared with the traditional constellation diagram after normalization, indicates that the proposed scheme is less tolerable to low SNR.

3. Simulation and Experiment setup.

The performance is firstly investigated through simulation. We assume the preprocessing tasks have been accomplished, such as carrier recovery, equalization etc. Six formats symbols are generated at SNR=3k (k=0,1,2...5) dB, each format has 1000 RGB images with 224×224 resolution, and 20% of 36000 images are test set. We use GoogLeNet V3 as CNN model and train it on NVIDIA GTX1050i GPU with the support of tensorflow libraries. The training process last more than 10000 epochs, the batch size is 128, keep probability is 0.8, the learning rate is adjusted from 0.1 to 0.01 gradually. We use cumulants method [5] as performance reference, the threshold ranges of cumulant C40 and corresponding classification are depicted in Table 1.



We firstly investigate the optimal symbol number of the proposed scheme. As is shown in Fig.2(a), the classification accuracy increases with the raw symbols used in one image, the trend slows down as the number of raw symbols exceeds 150, the accuracy rate achieves ~77% at 300 raw symbols per image. The performance of different methods is investigated under different SNRs, images made of raw symbols and pseudo symbols are trained and tested with GoogLeNet separately, the cumulant method calculate the cumulant C40 of the raw symbols. As is shown in Fig.2(b), the accuracy rate of all methods increases with the SNR, the GoogLeNet model using 1000 raw data achieves the highest classification accuracy under all SNRs, but in the range SNR > 11dB, the proposed scheme exceeds the cumulant method and achieves 98% accuracy rate at SNR=15dB, very close to that of GoogLeNet model. Of the proposed scheme, the accuracy rate using 300 symbols keeps about 5% higher than that of 150 symbols, indicates that more data enhance the statistics features and improve the performance. The confusion matrix of proposed method at 12dB SNR is shown in Table 2. the high order QAM formats have the most classification error, they are easily confused at low SNR.

Fig. 3(a) shows the experimental setup of the VLC system, the devices used are depicted in Table 3. The SNR of the VLC channel is firstly estimated by transmitting QPSK OFDM signals, the bit-loading algorithm decides the modulation formats of 60 subcarriers within the ~12MHz bandwidth. In the fading channel with SNR range from 8 to 23dB, M-QAM ($M=2^k$, k=2...6) formats are selected to guarantee that the BER of each subcarrier is lower than the FEC limit (5×10^{-3}) and the overall BER is lower than 3.8×10^{-3} . The parameters of OFDM frame are depicted in Table 4, each subcarrier loads 75 symbols in one frame, and generates one image with the proposed scheme. For each subcarrier, 1274 images are generated, and 30484 of the 76440 images are used for training.



Tabel 3 .Configuration of Devices	
AWG	Tektronix AWG7122B
LED	OSRAM LUW W5AM
PD	Hamamatsu S6968
Oscilloscope	Tektronix DPO4104B

Tabel 4. Configuration of OFDM Frames

FFT size	256
Frame length	150
Used subcarriers	60
CP	16
TS	11
Sampling rate of AWG	50-MSa/s
Sampling rate of Oscilloscope	250-MSa/s

Fig.3. Experimental setup of the VLC system. AWG: arbitrary waveform generator; PD: photodiode; TIA: transimpedance amplifier; OSC: oscilloscope

3. Results and discussions



Fig.4. (a) SNR measured and SNR threshold of the subcarriers. (b) Accuracy rate of different methods vs. the subcarrier index.

Fig.4(a) shows the SNR measured and the SNR threshold of each subcarrier, the insets are pseudo constellation images using 75 raw symbols. For each format, the measured SNR is higher than the SNR threshold of required BER, and the distinctive feature can be easily recognized. Fig.4(b) shows the classification results of different methods, the proposed scheme classifies the modulation formats with the accuracy rate 100%, deep learning and adequate pseudo symbols enhance the performance significantly. The cumulant method achieves much lower accuracy rate for 64-QAM, 16-QAM and 4-QAM with hundreds of raw symbols, the performance improves little as the symbol number increases, due to their close value of C40.

5. Conclusions

We proposed a modulation classification scheme based on deep learning and experimentally demonstrate it in the VLC system. Simulation results show that the proposed scheme achieves 98% classification accuracy rates for six modulation formats vary from 4-QAM to 64-QAM, experiments demonstrate that the modulation formats of each DMT subcarrier can be 100% correctly classified using 75 received symbols at BER threshold. The accuracy rate is higher and stable than that of cumulant method, with less received data.

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6. References

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