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Transmission Parameter-based Demodulation in Visible Light Communications using Deep Learning

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Abstract

This paper proposes an innovative approach by employing a one-dimensional Convolutional Neural Network (CNN) for demodulation in VLC systems. The used Data-set is real and available online, providing a robust foundation for analysis. It encompasses modulated signals in seven different modulation types, with 29 transmission distances ranging from 0 to 140 centimeters. By accounting for the varying distances between the transmitter and receiver, the model can more accurately interpret the received signals. Additionally, the study suggests that utilizing memory to learn previous symbols, which is essential for mitigating the effects of inter-symbol interference (ISI), can significantly improve demodulation accuracy. Our results of memory-based demodulation show a better performance in contrast to the previous one (AdaBoost).

Keywords: Demodulation; VLC; Distances; Convolutional Neural Network; ISI.

1- Introduction

Today, due to the fast development of electronic and digital devices, we are facing a familiar problem called the increase of wireless data traffic. One of the solutions is fast wireless transmission [1][2]. Visible Light Communication (VLC), due to its advantages such as unregulated spectrum, excellent security, and stability to electromagnetic interference, has been considered by researchers in the field of short-range fast wireless communications [3].

The accurate positioning is difficult in indoor optical communication scenarios [4]. There are several indoor positioning technologies to achieve the desired result, such as Global Positioning System (GPS), infrared, Ultra-Wideband (UWB), ultrasonic, etc. Although these technologies have high accuracy in positioning, most require specialized infrastructure that leads to high costs [5]. Other cases of indoor positioning, such as radio frequency identification (RFID) and Wi-Fi, can be affected by mutual interference and multi-path effects; therefore, high-accuracy positioning cannot be achieved. Recently, indoor positioning has been accepted as a promising candidate in VLC [6]. To achieve better positioning performance, the machine learning (ML) method can be introduced in indoor positioning with VLC [7].

ML-based model-free demodulators are becoming popular, where the need for prior knowledge can be eliminated. In the modulation process, the phase and amplitude of the signals are modulated [8]. Recently, much work has been done in VLC applications using ML, and we will review some of them. Ma et al. [9] studied three types of demodulators based on ML methods in VLC, including eight modulation types. Their proposed convolutional neural network (CNN) model receives images generated using the modulated signals and recognizes the signal by image classification. In [10], they proposed a semi-supervised self-trained large margin classifier to track and classify popular single carrier modulations in nonstationary environments, demonstrating robust performance even in low SNRs. In [11], K. Majeed et al. have done comprehensive research on indoor positioning for VLC, in which the combination of multiple classifiers, including KNN, RF, and ELM, was studied. They have shown that by increasing the distance, the positioning accuracy decreases. Lin et al. [12] proposed the CNN in the NOMA-VLC system, in which signal compensation and retrieval are performed jointly, which can improve the distortion caused by multi-directional scattering. Shi et al. [13] presented ML-based techniques for communication signal demodulation. These techniques are used in channel estimation and traditional decision-makers.

In [6], demodulation is used for carrier-less amplitude-phase (CAP) modulation, which is a significant modulation. Also, criteria such as accuracy, bit error ratio (BER), and signal-to-noise ratio (SNR) have been investigated; experimental results show that CAP- VLC-based systems

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result in better performance, including 92.4 % accuracy in various conditions and increased BER. In [14], M-QAM (M = 16, 32, 64, 128, 256), OOK, QPSK, 4-PPM, modulation schemes have been investigated, and in addition, two DL-based demodulators and AdaBoost have been proposed.
However, in [9], the images are used as data, and the demodulation accuracy is not high and acceptable; also, in [11] [12], the complexity is high, and the accuracy is low due to the use of multiple classifiers for positioning. The disadvantages of [13] and [10] are that the demodulation accuracy depends on SNR, and the distance is not considered.
In this paper, for the first time, we have applied distance information in signal demodulation; therefore, the network can learn and benefit from it to increase signal demodulation accuracy. Joint demodulation and ranging are performed using 1D-CNN, in which the signal sequence is considered the network input. The sequence is a one-dimensional input that needs a simpler network than the neural networks, which take the images as input data. Moreover, real VLC data with 29 different distances and seven modulation types are used to evaluate the performance of the proposed method.
In the proposed network, each label is equivalent to a modulation level and its distance, and by classifying a symbol, demodulation and its distance are determined. This dual capability significantly streamlines the process, making it more efficient and accurate.
The proposed 1D-CNN can increase the demodulation accuracy by applying memory and distance information, specifically for higher-order modulations and long distances. This is particularly important in VLC systems, where signal degradation can be significant at greater distances and higher modulation orders. The inclusion of memory helps the network to understand the signal context better, improving its ability to demodulate accurately. Furthermore, our method simplifies the network design while maintaining high performance, making it a practical solution for real-world VLC applications.
Additionally, we explored various configurations of the network to optimize its performance. By adjusting parameters such as the length of the input sequence and the depth of the network, we were able to find the best settings that maximize accuracy. The results from our extensive simulations show that our approach not only outperforms traditional methods but also offers a robust solution that can adapt to different environmental conditions and modulation schemes.
Integrating of distance information and memory into the 1D-CNN represents a significant advancement in the field of VLC. This approach increases demodulation accuracy and provides a comprehensive framework for addressing common challenges in optical wireless communications. The use of real-world data further validates the effectiveness of our method, demonstrating its potential for deployment in practical scenarios. Future work could expand on this foundation by exploring additional ways to leverage contextual information and improve network architecture, paving the way for even more sophisticated and reliable VLC systems.

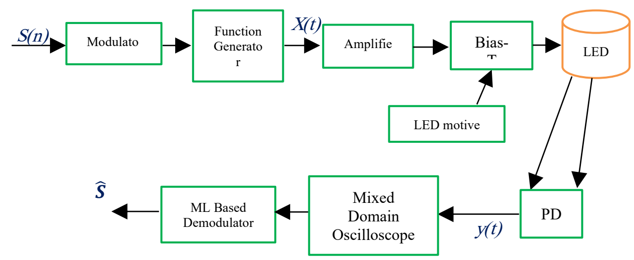

Fig 1: Demodulation based on ML of VLC [9].

2- Methodology

The system model used in this study is identical to that of [9], which is briefly illustrated in Fig. 1. For more detailed information, please refer to [9].

2-1- Data-set

The used data set generated in real physical environments is accessible via https://pan.baidu.com/s/1rS143bEDaOTEiCneXE67dg [9] in seven modulation schemes: 16-QAM, 32-QAM, 64-QAM, 128-QAM, 256-QAM, OOK, and QPSK. 29 transmission distances ranging from 0 cm to 140 cm are considered for the seven modulated signals. There are four different numbers of sample points (N = 10, 20, 40, 80) in each period for every modulation scheme. Lengths of signals according to the total number of periods in each case are listed in Table 1.
It can be seen from Fig. 2 that all 16 labels of 16-QAM have no similarity in amplitude and phase.

2-2- Network Structure

Due to the simplicity and high efficiency of the CNN network, we used this type of network for demodulation. The distance information of the received signal is used for demodulation; the different distances can have specific features, such as SNR, which can help the demodulation process. Furthermore, it is important to note that the sequence of the received signal serves as the singular input for the network. By utilizing this one-dimensional input, a more straightforward neural network can be constructed compared to those designed for two- or three-dimensional

images. This is due to the fact that signals represented in image form often contain extraneous and redundant information. The intricacies of the model put forth are delineated further in the subsequent discussion.
In this research, a series of signals is regarded as the fundamental input data for a demodulator rooted in Convolutional Neural Network technology. The dimensions of each input vector are inherently contingent upon the signal's specific sampling rate. Delving deeper into this discourse, the innovative CNN architecture being presented comprises four meticulously crafted convolutional layers, a pivotal Global Average Pooling layer, and two intricately designed fully-connected layers. These convolutional layers serve as vital components aimed at extracting imperative features from the input data by employing filters of varying sizes. Moreover, it is crucial to mention that the depth of these filters has been discerningly determined with precision based on the unique characteristics inherent within each individual convolution layer, thus encapsulating an intricate level of complexity as delineated in.Eq. (1):

$$y_k^l = b_k^l + \sum_{i=1}^{N_{l-1}} w_{ik}^l * x_i^{l-1} \quad (1)$$

Where y_k^l and b_k^l denote the *k-th* feature map and its bias in layer *l*, x_i^{l-1} is the *i-th* feature map in layer *l-1*, w_{ik}^l is the weights from *i-th* feature map in layer *l-1* to the *k-th* feature map in layer l, (*) represents the convolution operator and N_{l-1} is the number of feature map in layer *l-1* [15].
The Global average pooling layer reduces the number of parameters that can be trained during model learning [16] [17]. In the realm of Classification, SoftMax activation performs two classes in the fully connected layer. As mentioned, these two types each represent two parameters; The estimated distance and the desired modulation symbol number will result in 29*L classes, where L is the number of desired modulation labels. For example, we have 29*32 classes in 32-QAM. Each class is related to a modulation label and its distance. At this layer, the learning method uses feed-forward and back-propagation algorithms [18].
The Leaky RELU is applied as the activation function for all convolutional layers, and in the last layer, the SoftMax function is used. In the RELU activator function, some neurons die or become inactive, and the output becomes zero. To solve this issue, a function called Leaky RELU is used, which prevents the death of neurons with negative values. In our proposed CNN, the Leaky ReLU activation function is employed instead of the standard ReLU. While ReLU is widely used due to its simplicity and effectiveness in mitigating vanishing gradients, it suffers from the "dying ReLU" problem, where some neurons output zero for all inputs and stop learning during training. To address this, Leaky ReLU introduces a slight negative slope (e.g., 0.1x) for inputs less than zero, ensuring that all neurons propagate gradients during backpropagation. This modification enhances the model's learning capability and stability, especially in deep architectures. The choice of Leaky ReLU is based on empirical tests, which showed more consistent convergence and slightly improved accuracy compared to standard ReLU. The Leaky RELU formula is according to Eq. (2):

$$f(x) = \max(0.1x. x) \quad (2)$$

The SoftMax function calculates the probability associated with each output, and this type of function is used in the last layer of the network and gives the output probability. So, the sum of the probabilities = 1 [9]. The SoftMax formula is based on Eq. (3):

$$softmax\,(z_i) = \frac{\exp\,(z_i)}{\sum_{j=1}^{K} \exp\,(z_j)} \quad (3)$$

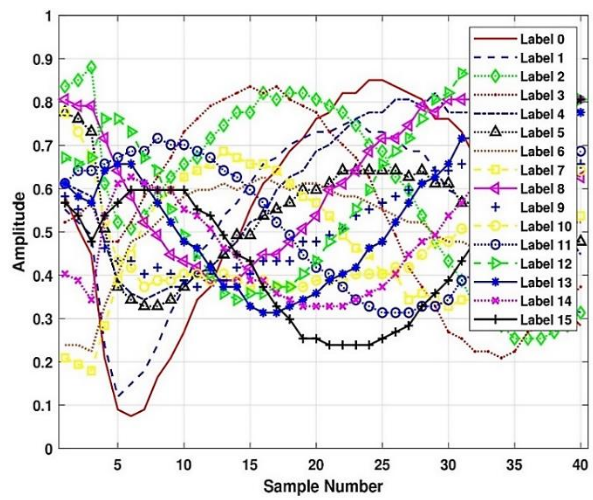

Fig 2: Some samples of 16-QAM signal

The structure of the proposed network is shown in Fig. 3, and the details of the proposed model are described in Table 2. The input signal is fed to the Conv-1 layer with 38 filters, generating 38 feature maps; then, Batch-Normalization is utilized. The same operations are applied to all four layers but with different filter sizes and numbers. Finally, the Global average pooling layer is connected to the fully connected layer. The multi-path propagation channel is one of the main challenges in indoor OWC. A reflected signal will have a slight delay and reduce all signal levels except the LOS links. However, the signal reaches the Rx through different paths, with various delays and attenuation.
In this paper, we add memory to the CNN network to increase the accuracy and efficiency of the system for demodulation and distance estimation. We propose to employ the information of previous symbols on the current signal by adding them to the input signal sequence.

Finally, we randomly separate 70% of the training data, 20% for test data, and 10% for validation data.

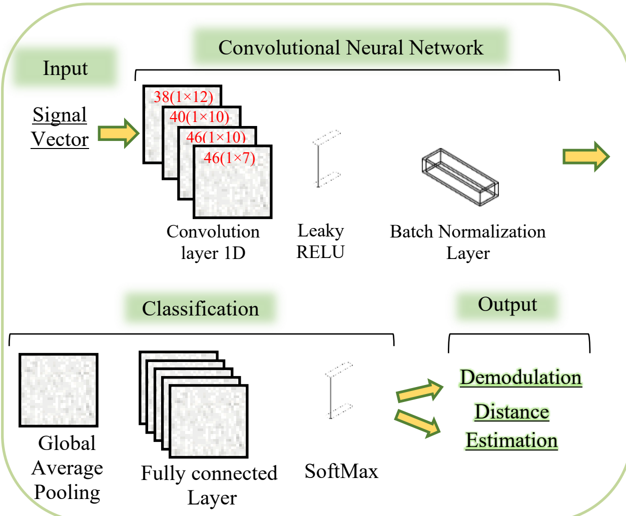

Fig 3: The structure of the proposed network

2-3- Performance Evaluation and Implementation Detail

In this paper, we have performed demodulation and distance estimation for M-QAM (M = 4, 16, 32, 64, 128, 256) and OOK modulations at 0 to 140 cm (for 29 distances). The proposed CNN was implemented for four different values of N = 10, 20, 40, and 80, where N represents the number of signal samples in each period. In this experiment, the batch size is set to 3500, the epoch number ranges from 100 to 200, and the Adam method is used as the optimizer. The network measurement criterion for this work is the accuracy of demodulation. All the proposed methods are implemented with MATLAB R2021b and executed on a computer with an Intel Core i7-4200 CPU @ 1 GHz/8GB RAM.

The choice of these specific parameters was made after extensive experimentation to ensure optimal network performance. Varying values of N allowed us to observe how the number of signal samples affects demodulation accuracy, providing insights into the optimal configuration. The batch size of 3500 ensured efficient training, and the range of epochs (100 to 200) balanced training time with performance, preventing overfitting.

The Adam optimizer facilitated fast and stable convergence, handling sparse gradients and adaptive learning rates effectively. Despite the modest computational setup, the Intel Core i7-4200 CPU and 8GB of RAM were sufficient for training and testing the CNN. Supplementary tests, including varying modulation schemes and distances, adjusting batch sizes, and experimenting with optimizers, reinforced our findings

3- Discussion and Results

Table 2: The parameters of the CNN

Layers	*Filter Size*	*Number of Filters*
Conv-1	1×12	38
Conv-2	1×10	40
Conv-3	1×10	46
Conv-4	1×7	46

3-1- Discussion

We have to specify that for demodulation and distance estimation, we used real normalized data provided by [9]. In the data, d is the distance between the LED and PD, and it is collected every 5 cm from d = 0 cm to d = 140 cm and normalized. This data-set can be helpful for commenting on examples of how approaches perform under various circumstances. Nonetheless, there are still many research topics left to be explored in the VLC system, more specifically, concerning the channel modeling. Performance can be enhanced when the system is designed to incorporate selected machine learning (ML). Therefore, using DL, and specifically, the CNN architecture, we succeeded in demodulating seven different modulations, among which M-QAM (M = 4, 16, 32, 64, 128, 256), and OOK in VLC.

The simulations were carried out in MATLAB; first, distance was estimated, and then demodulation was done. In order to increase the experiment accuracy, we used memory in the CNN for the previous symbols that influenced the current symbol. First, the network was trained for 32-QAM with a lesser distance using 1D-CNN to design the basic classifier. Optimum demodulation accuracy of the transmitted information was obtained by fine-tuning of the various network parameters. This approach aimed to extend the length of the 1D input sequence where two previous signals are added to the current one, making the input 3-channels (3-ch).

To analyze the effect of changes in memory and size of the input sequence, we trained the proposed network with the 5-ch, 8-ch, 10-ch, and 12-ch input data arrangements. It is worth noting that although explicit experiments with controlled SNR values were not conducted, the data-set inherently reflects a range of SNR conditions through the variation of transmission distances. As distance increases from 0 cm to 140 cm, the received signal power decreases, effectively reducing the SNR. Also, the data-set is collected under real conditions. It is true that for different distances, SNR changes, but since the data-set is real, we do not have SNR. Last but not least, we examined modulation accuracy when the channel is specified with different parameters. In order to evaluate the correctness of the discussed CNN-based demodulation method considering 32-QAM modulation, the distance-dependent results are shown in Fig. 4 for different values of N = 10, 20, 40, 80. This analysis likewise shows a clear trend of the modulation accuracy for N = 40 outcompeting the others, hence supporting the conclusion of [9]. The choice of input sequence length N is crucial in balancing demodulation accuracy and real-time processing feasibility. While larger values of N (e.g., 40 or 80) capture more signal context and improve classification accuracy, they also increase the computational load and inference latency. In contrast, smaller N values (e.g., 10 or 20) are faster to process but yield lower accuracy, as shown in our comparative results. Therefore, N=40 was selected as a practical trade-off, offering reliable demodulation and acceptable complexity for real-time applications.

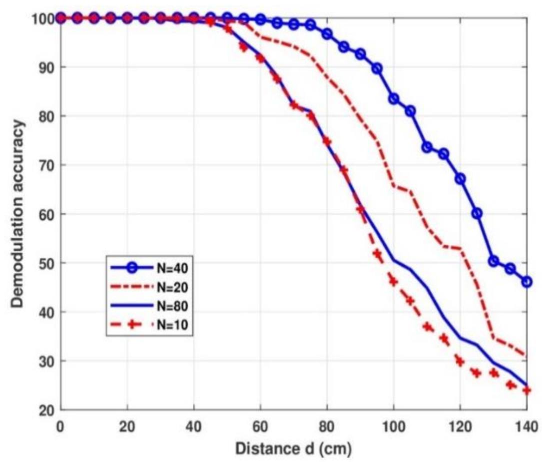

Fig 4: The demodulation accuracy of CNN versus distance *"d"* in diferent sample points.

Fig. 5 shows the demodulation accuracy of 32-QAM with distance relation in (d) for N=40 in order to assess the influence of memory on the performance. The accuracy is much higher when demodulating with more than one channel up to 10 channels (10-ch). Also, the probability for eradicating the virus is much higher in the early stage of its spreading. Coefficients for 32-QAM are N= 40, ch= 10; furthermore, experiments showed that. Therefore, the simulations are performed for N=40 and ch =10. The network training is illustrated based on the demodulation accuracy of the CNN demodulation method in Fig. 6.

Depicted below are the accuracy levels obtained for the 16-QAM as well as 32-QAM configurations of the classifiers; it is evident that there is better accuracy for the 16- QAM than the 32- QAM and after achieving a success rate of about 75 % after 150 epochs the models exhibit steady performance.

These results clearly will open the potential of the proposed CNN-based demodulation technique to improve the precision and dependability of VLC systems. It is also believed that in the future, one might investigate the usage of this method in other forms of modulation and more complicated systems and scenarios in OWCs.

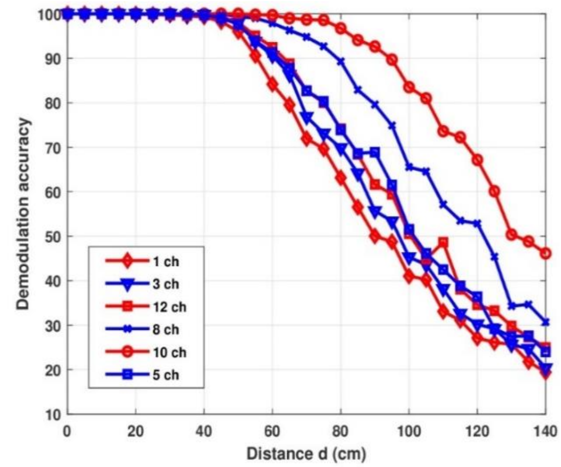

Fig 5: The demodulation accuracy of 32-QAM modulated signals versus distance d in: 1ch, 3 ch, 5 ch, 8 ch, 10 ch, 12 ch when N = 40.

To show the efficiency, it is necessary to explain that we tested different methods to reach the final result, which is reported in the article. Here, the main discussion is on the effect of memory and distance on demodulation accuracy; thus, we can have two types of networks besides the proposed method:

1. A network without any information from the last symbols.
2. A network where the distance effect is ignored.

This network demodulates only at one determined distance, and different networks are trained for each distance. In the first case, we have a regular and basic network, and the results are similar to the CNN-based demodulator referenced in [9]. Consequently, the accuracy is lower than that achieved by Adaboost, demonstrating the limitations of this approach when memory is not considered.

In the second case, the problem involves training a distance estimator before demodulation. This approach requires an additional step of accurately estimating the distance before demodulating the signal. The challenge here is that the error in distance estimation directly affects the symbol demodulation accuracy. If the distance estimator introduces errors, these errors will compound the demodulation error, leading to a significant degradation in performance. This method highlights the critical nature of accurate distance information in achieving high demodulation accuracy.

To further illustrate the benefits of the proposed method, we conducted extensive simulations comparing these network types with the proposed approach, which incorporates both memory and distance information. The results clearly showed that the proposed method outperforms the other two types of networks. By including the memory of previous symbols, our network effectively mitigates ISI, leading to higher accuracy. Additionally, considering the distance information, the network adapts better to varying conditions, further enhancing performance.

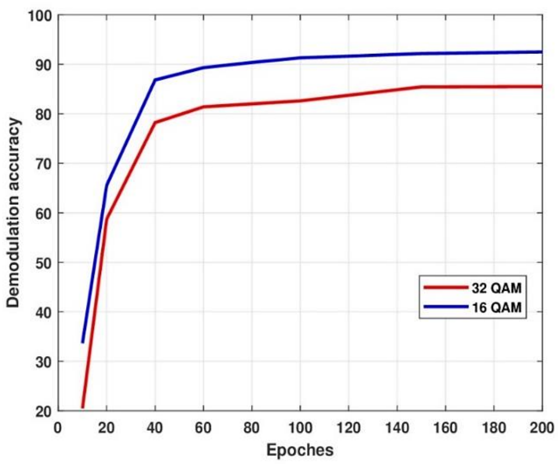

Fig 6: The demodulation accuracy of CNN based method with respect to epochs when N = 40 and 10 ch, d= all distance.

Moreover, we explored the effect of different memory lengths and how they influence the demodulation accuracy. Longer memory lengths generally led to better performance up to a certain point, beyond which the computational complexity increased without significant gains in accuracy. This finding suggests an optimal balance between memory length and computational efficiency, which is crucial for practical implementations.

Furthermore, the proposed method's robustness was tested across various modulation schemes and environmental conditions. It consistently demonstrated superior performance, underscoring its versatility and reliability. The comprehensive analysis and comparison provided in the article highlight the significant advancements made by incorporating memory and distance information into the demodulation process, paving the way for future research and development in this field.

In conclusion, our findings emphasize the importance of memory and distance information in achieving high demodulation accuracy in visible light communication systems. The proposed CNN-based approach substantially improves over traditional methods, providing a robust and efficient solution for practical VLC applications. Future work could focus on further optimizing the network parameters and exploring its application to even more complex scenarios, ensuring continued progress in this rapidly evolving field.

3-2- Results

From the results obtained, the demodulation accuracy reduces with the order of modulation and distance. In [9], the CNN, AdaBoost, DBN classifiers are employed to demodulation, and it is identified that AdaBoost was most accurate. A comparison between the proposed method and AdaBoost regarding demodulation accuracy is illustrated in Fig. 7. The analysis proves that improving accuracy can be achieved using information of distance and previous symbols. It is evident that at a distance of 140 cm, the augmentation in the accuracy can be over 50%. This is a big leap forward from the earlier procedures. The proposed network is extended to other modulations, and the results are shown in Fig. 8. As observed here, as the distance increases when employing higher-order modulation, the number of errors in the demodulation also increases.

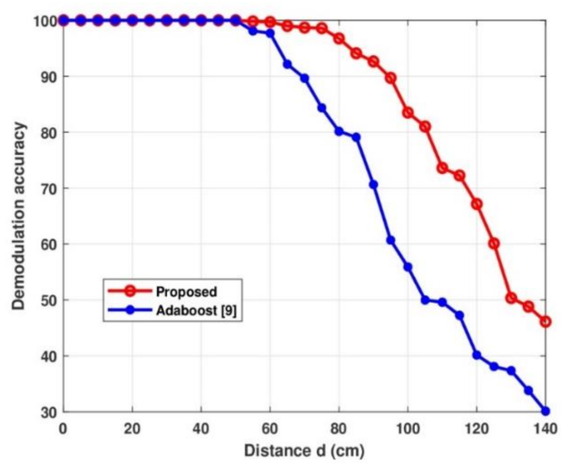

Fig 7: The demodulation accuracy of CNN based method for 32- QAM.

As shown in Fig. 8, the demodulation accuracy of the seven modulation schemes is inversely proportional to the distance d. Also, in M-QAM type systems, when the modulation level increases and for a fixed distance d, accuracy decreases even more. This indicates the difficulties encountered in ensuring high levels of accuracy of VLC systems with higher-order modulations and larger distances. This indicates that the proposed method can effectively address these problems by making use of distance and historical symbol information, which adds to the idea that the method can improve VLC system performance in real-world applications. This may be an area of interest where improved algorithms are sought for tackling more complicated problems and modulation types.

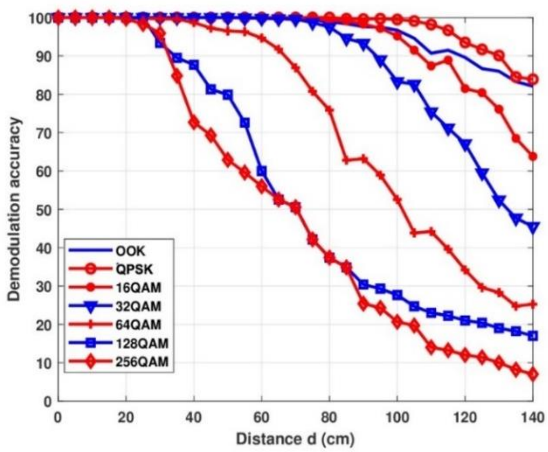

Fig 8: The demodulation accuracy of OOK, QPSK, 16-QAM, 32-QAM, 64-QAM, 128- QAM and 256-QAM modulated signals with respect to distance d when N = 40,10 ch.

4- Conclusions

TIn this research, the CNN was suggested in signal demodulation of VLC system that reveals its promising future. Testing the proposed method with a veritable dataset containing seven different modulations and 29 separate distances, the investigation of demodulation performance was quite accomplished. Other important parameters such as distance information were revealed to further improve the demodulation BER performance. Therefore, the number of inputs was chosen so that the network capacity was gradually adjusted to the best possible state.
Simulation results given in figures also showed that the proposed demodulator outperforms the existing conventional demodulator by a large margin. For example, at 140 cm distance the improvement for demodulating 32-QAM can go beyond 50%. This big advancement shows that integration of distance and historical symbol information into demodulation exercise is very efficient.
Moreover, analyzing the performance of the proposed CNN demodulator by applying it to different modulation schemes as well as distances, it can be concluded that improved performance is achieved. From these results, it can be concluded that the method is very flexible and, even when placed under extreme conditions, provides a high level of accuracy. However, it can be suggested that the future work could be done to investigate the further application of this approach to the more high-order modulation scenarios or the more complicated modulation environments. Furthermore, one can incorporate enhanced methods like learning rate adaptation and other advanced structures of the neural networks, which might result in further enhanced levels of demodulating efficiency. The findings of this particular study will illuminate other enhanced performances of the VLC system and will be helpful in improving such technologies as revealed in this research.

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