Intelligent Index Recognition for OFDM With Index Modulation in Underwater OWC Systems

Xinyue Zhang, Zhihong Zeng, Pengfei Du, Bangjiang Lin, *Senior Member, IEEE*, and Chen Chen, *Senior Member, IEEE*

***Abstract*— Orthogonal frequency division multiplexing with index modulation (OFDM-IM) is a promising scheme for underwater optical wireless communication (UOWC) due to its high power efficiency and flexibility. In this letter, we propose and experimentally demonstrate an intelligent index recognition scheme for OFDM-IM in UOWC systems. Considering the unique activation patterns of OFDM-IM with different numbers of activated subcarriers within each subblock, the signal histograms in the frequency domain are adopted as the features for recognition. Moreover, various machine learning or deep learning algorithms are further utilized as the tools to perform intelligent index recognition based on the distinctive frequency-domain histograms. Experimental results demonstrate the feasibility of the proposed intelligent index recognition scheme for OFDM-IM in UOWC systems. In addition, the impact of the number of bins and the number of symbols on the performance of index recognition is also studied.**

***Index Terms*— Orthogonal frequency division multiplexing with index modulation (OFDM-IM), index recognition, underwater optical wireless communication (UOWC).**

I. Introduction

UNDERWATER optical wireless communication (UOWC) has been widely considered as a promising technology to realize the sixth-generation (6G) underwater communication in recent years, due to its abundant spectrum resources, low link delay, high communication security, large transmission capacity and low implementation cost [1], [2]. Nevertheless, practical UOWC systems are generally bandlimited due to the low-pass nature of the optical components such as light-emitting diodes (LEDs), laser diodes (LDs) and photodetectors (PDs) [3]. Moreover, the underwater channel can also be very complex and dynamic, which requires high flexibility to implement UOWC in practical applications [4].

As an enhanced version of classical orthogonal frequency division multiplexing (OFDM), OFDM with index modulation (OFDM-IM) has been recently proposed as an efficient technique to improve the power efficiency and flexibility of OFDM [5], which has also been applied in UOWC systems [6], [7]. Improved OFDM-IM such as coordinate interleaved OFDM-IM has been further designed to enhance the performance of OFDM-IM [8], [9]. The basic principle of OFDM-IM is to group subcarriers into subblocks and selectively activate a subset of subcarriers within each subblock to transmit both constellation symbols and index bits. When applying OFDM-IM in complex UOWC systems, the number of activated subcarriers within each subblock can be dynamically adjusted to adapt to the various underwater channels conditions.

To perform OFDM-IM demodulation, the exact number of activated subcarriers needs to be known at the receiver side [10]. Considering the practical underwater channel can be complex and dynamic, the number of activated subcarriers within each subblock might change with time in OFDM-IM based UOWC systems. Hence, it is of practical significance to enable index recognition at the receiver side before carrying out signal demodulation. Recently, likelihood-based and deep neural network (DNN)-based index recognition schemes have been reported [11], [12]. Nevertheless, likelihood-based index recognition involves high-complexity likelihood ratio calculations, while DNN-based index recognition requires a large number of samples for successful training. To the best of our knowledge, efficient OFDM-IM index recognition in UOWC systems has not yet been reported in the literature.

In this letter, we propose an intelligent index recognition scheme for OFDM-IM in UOWC systems by exploiting the signal histograms in the frequency domain as the recognition features. Moreover, machine learning and deep learning algorithms including decision trees (DT), support vector machine (SVM), k-nearest neighbors (k-NN) and convolutional neural network (CNN) are applied to perform intelligent index recognition based on the histograms. Hardware experiments are conducted to verify the feasibility of the proposed intelligent index recognition scheme for OFDM-IM in UOWC systems.

II. Principle

In this section, we first introduce the principle of OFDM-IM in UOWC systems, and then the adopted recognition features and recognition algorithms for intelligent index recognition are further discussed, respectively.

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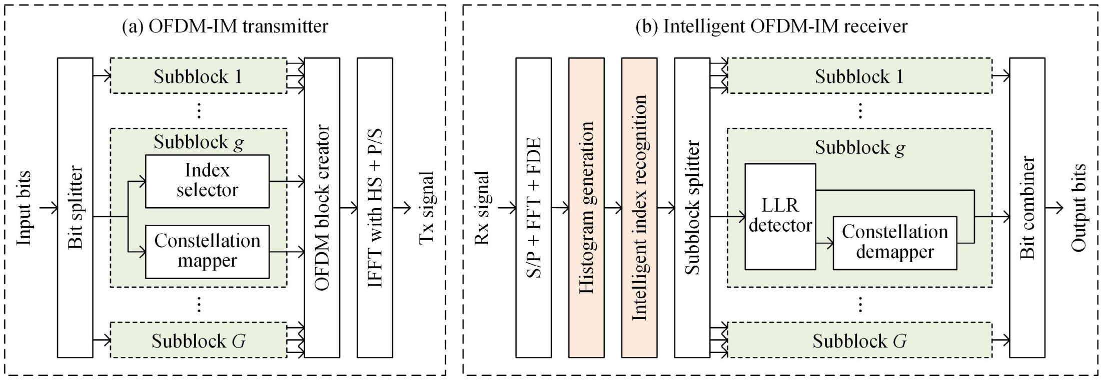

Fig. 1. Schematic diagram of the OFDM-IM system with intelligent index recognition: (a) OFDM-IM transmitter and (b) intelligent OFDM-IM receiver.

TABLE I
MAPPING TABLE FOR $n = 4$ AND $l \in \{1, 2, 3\}$

Scheme	Index bits	Subblocks
$n = 4, l = 1$	0 0	$[S_i, 0, 0, 0]$
	0 1	$[0, S_i, 0, 0]$
	1 1	$[0, 0, S_i, 0]$
	1 0	$[0, 0, 0, S_i]$
$n = 4, l = 2$	0 0	$[S_i, S_j, 0, 0]$
	0 1	$[0, S_i, S_j, 0]$
	1 1	$[0, 0, S_i, S_j]$
	1 0	$[S_i, 0, 0, S_j]$
$n = 4, l = 3$	0 0	$[S_i, S_j, S_k, 0]$
	0 1	$[0, S_i, S_j, S_k]$
	1 1	$[S_k, 0, , S_i, S_j]$
	1 0	$[S_j, S_k, 0, S_i]$

Figs. 1(a) and (b) depict the diagrams of the OFDM-IM transmitter and receiver, respectively. At the OFDM-IM transmitter, the input bits are first divided into G groups via a bit splitter and each group of bits are then sent into a subblock, where N subcarriers are divided into G subblocks and the subblock length is $n = N/G$. In each subblock, the group of bits are split into two parts which are used to perform index selection and constellation mapping. For each subblock, l out of n subcarriers can be selected to transmit constellation symbols, with $l \in \{1, 2, \cdots, n\}$. More specifically, OFDM-IM becomes conventional OFDM when $l = n$ [10], [13]. The mapping table of OFDM-IM with $n = 4$ and $l \in \{1, 2, 3\}$ is given in Table I, where S_i, S_j and S_k denote the transmitted constellation symbols. After that, the OFDM block is created by combining all the subblocks together. Due to the intensity modulation nature of general UOWC systems, inverse fast Fourier transform (IFFT) with Hermitian symmetry (HS) is executed to obtain a real-valued OFDM signal to modulate the light intensity of LED/LD transmitters in UOWC systems [7]. Finally, the resultant parallel signal is converted to a serial signal via parallel-to-serial (P/S) conversion.

At the intelligent OFDM-IM receiver, the received signal is first converted to a parallel signal through serial-to-parallel (S/P) conversion. Then, fast Fourier transform (FFT) and frequency domain equalization (FDE) are further carried out. As discussed above, the number of subcarriers that can be activated for signal transmission can be varied from 1 to n, i.e., $l \in \{1, 2, \cdots, n\}$, and hence the correct signal detection in each subblock requires the accurate information about the l value. For the intelligent OFDM-IM receiver, the l value can be recognized via intelligent index recognition. More specifically, the histograms of the frequency-domain signal after FDE are first counted, which are then used as the feature values for subsequent intelligent index recognition using machine learning or deep learning algorithms. The detailed principle about the adopted recognition features and recognition algorithms will be discussed in the following subsections. After intelligent index recognition, the OFDM block is split into G subblocks and low-complexity log-likelihood ratio (LLR) detection can be performed to recover the index bits and extract the constellation symbols for constellation demapping. The final output bits can be obtained by combining the generated bits of each subblock together.

To realize index recognition, frequency-domain histograms of the received signal are adopted as the recognition features to perform intelligent index recognition. Since the signal obtained after FFT and FDE is complex-valued, we utilize the absolute and normalized values of the complex-valued signal to generate the histograms. Letting X^z denote the received complex-valued signal vector of the z-th OFDM symbol in the frequency domain, the resultant signal after taking the absolute value and normalization can be expressed by

$$\hat{X}_i^z = \frac{|X_i^z| - |X^z|_{\min}}{|X^z|_{\max} - |X^z|_{\min}},\ \ i = 1, 2, \cdots, N, \tag{1}$$

where $|\cdot|$ represents the operation to take absolute value of a complex-valued input, and $|X^z|_{\max}$ and $|X^z|_{\min}$ denote the maximum and minimum absolute values of the elements in the signal vector X^z, respectively.

Due to the normalization process in (1), the amplitudes of the elements in the obtained signal vector $\hat{X}^z$ are all within the range from 0 to 1. As a result, by dividing this range into H amplitude intervals, we can convert the normalized signal vector $\hat{X}^z$ into a histogram with H bins by counting the number of elements falling within a certain amplitude interval. Moreover, we can also utilize multiple OFDM symbols together to generate the signal histograms so as to mitigate the adverse effect of the additive noise. Here, the number of OFDM symbols which are simultaneously utilized to generate the signal histograms is denoted by K. Fig. 2 illustrates the transmitted signal histograms without normalization and the received signal histograms with normalization for OFDM-IM using binary phase shift keying (BPSK) with $K = 1$, $H = 10$,

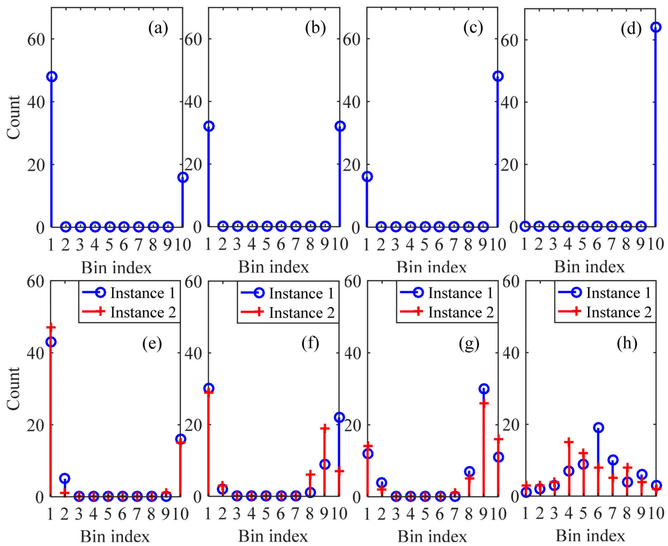

Fig. 2. Transmitted signal histograms without normalization for (a) $l = 1$, (b) $l = 2$, (c) $l = 3$ and (d) $l = 4$, and received signal histograms with normalization for (e) $l = 1$, (f) $l = 2$, (g) $l = 3$ and (h) $l = 4$.

$n = 4$ and different l values. Due to the distinctive subcarrier activation patterns for different l values, the transmitted signal histograms without normalization show quite different shapes for different l values. For the received normalized signal histograms with noise, the amplitudes of the elements are mostly located in the 1st and the 10th intervals for $l = 1$. When l is increased to 2 and 3, more amplitudes are located at the higher bin indexes while the count of the amplitudes at the bin index of 1 gradually decreases. For the case of $l = 4$, i.e., conventional OFDM, the amplitudes are generally distributed across all the bin indexes, with the highest counts observed at the middle bin indexes such as 5 and 6. It can be clearly seen from Fig. 2 that there is fundamental difference among the signal histograms for different l values, which can be efficiently utilized as features to perform intelligent index recognition for OFDM-IM in UOWC systems.

Based on the recognition features using signal histograms, the following machine learning or deep learning algorithms are considered to fulfill the recognition task in OFDM-IM based UOWC systems.

1) Decision Tree (DT): The DT with the C4.5 algorithm is utilized by sending the labeled histograms of four index formats as features for training, which uses the information gain ratio as a rule to select features and determine the index of each testing histogram [14].

2) Support Vector Machine (SVM): SVM with radial basis function is used to identify the H-dimensional space, enabling the recognition of four index formats using histograms [15].

3) K-Nearest Neighbors (k-NN): When applying k-NN, each testing histogram finds its nearest neighbors by calculating the Euclidean distance in H-dimensional space and then classifying them by a majority vote based on the index formats of these neighbors [16].

4) Convolutional Neural Network (CNN): A CNN model is also considered, which consists of two convolutional layers, two pooling layers, and two fully connected layers with 64 and 4 neurons, respectively [17].

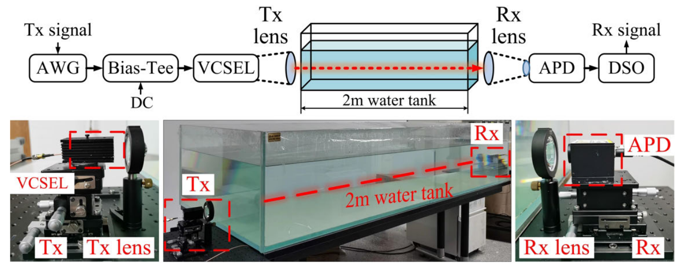

Fig. 3. Experimental setup of the UOWC system with a 2m water tank.

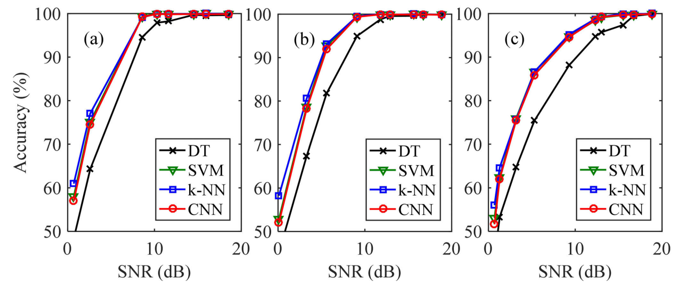

Fig. 4. Experimental accuracy vs. SNR with different recognition algorithms for OFDM-IM using (a) BPSK, (b) 4QAM, and (c) 8QAM.

III. Results and Discussions

To investigate the performance of the proposed intelligent index recognition scheme for OFDM-IM in UOWC systems, hardware experiments are conducted in the lab environments. Fig. 3 depicts the experimental setup of the UOWC system utilizing a vertical-cavity surface-emitting laser (VCSEL). At the transmitter side, the transmitted signal generated offline by MATLAB is first loaded into an arbitrary waveform generator (AWG) with a sampling rate of 4 GSa/s, where the IFFT/FFT size is 256, the number of data subcarriers is 64, the number of subblocks is 16 and the subblock length is 4. Hence, the effective bandwidth of the OFDM-IM signal is 1 GHz. Then, the signal is combined with a 2.3V direct current (DC) bias via a Bias-Tee to drive the VCSEL and a biconvex lens is used to focus the light for transmission through a 2m water tank. At the receiver side, another biconvex lens is used to focus the light onto the avalanche photodiode (APD). A digital storage oscilloscope (DSO) with a sampling rate of 12.5 GSa/s is further used to record the data for offline processing.

In the experiments, the training and testing histograms are generated following the method introduced in Section II.B, where four index formats (i.e., $l \in \{1, 2, 3, 4\}$) are set for recognition and three constellations including BPSK, 4-ary quadrature amplitude modulation (4QAM) and 8QAM are also considered for OFDM-IM. For each constellation, a total of 1600 histograms are generated for the four index formats with 400 histograms for each index format, where 80% of the histograms are used for training and the rest 20% of the histograms are used for testing.

Figs. 4(a), (b) and (c) show the recognition accuracy versus signal-to-noise ratio (SNR) with different recognition algorithms for OFDM-IM using BPSK, 4QAM and 8QAM, respectively, where $K = 1$ and $H = 10$. As we can see, the recognition accuracy is generally increased with the increase of SNR for all the recognition algorithms. Moreover, it can be seen that DT obtains the lowest accuracy while k-NN achieves

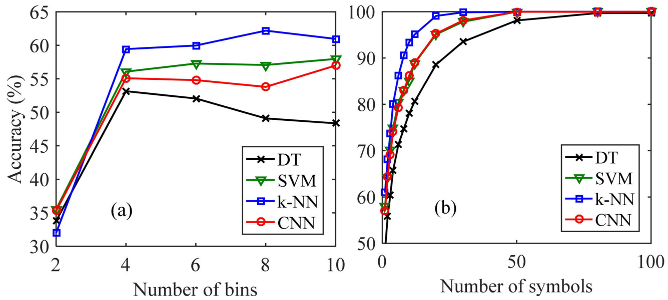

Fig. 5. (a) Experimental accuracy vs. number of bins and (b) experimental accuracy vs. number of symbols.

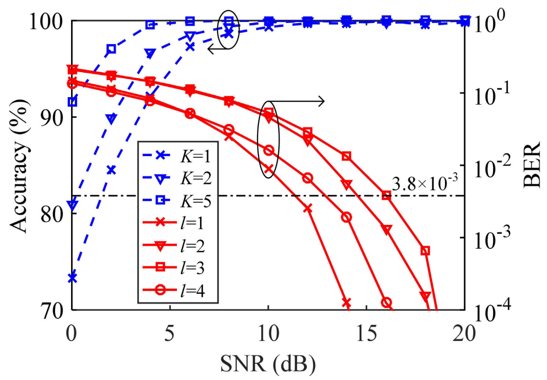

Fig. 6. Simulation accuracy and BER vs. SNR over an AWGN channel.

the highest accuracy among all the algorithms. In addition, CNN and SVM have nearly the same accuracy, suggesting that the use of deep learning algorithms such as CNN in this kind of recognition task might not achieve satisfactory performance. Furthermore, the required SNRs for BPSK, 4QAM and 8QAM using k-NN to reach near 100% accuracy are 8.6, 9.1 and 13 dB, respectively, indicating that a larger SNR is required for a higher order of constellation.

Fig. 5(a) shows the recognition accuracy versus number of bins with different recognition algorithms for OFDM-IM using BPSK, where $K = 1$ and SNR $= 0.7$ dB. As we can see, a total of four bins, i.e., $H = 4$, can be sufficient for all the algorithms to achieve stable performance. Fig. 5(b) shows the recognition accuracy versus number of symbols with different recognition algorithms for OFDM-IM using BPSK, where $H = 10$ and SNR $= 0.7$ dB. It can be seen that the use of more OFDM symbols to generate the histograms can lead to significantly improved recognition accuracy. Taking k-NN for example, the recognition accuracy is increased from 60.9% to 93.5% when the number of symbols K is increased from 1 to 10.

Fig. 6 shows the simulation accuracy and BER vs. SNR over an additive white Gaussian noise (AWGN) channel for OFDM-IM using BPSK with $H = 10$ and k-NN. With the increase of SNR, the BER gradually reduces while the recognition accuracy gradually increases. Specifically, an SNR of 11.4 dB is required for $l = 1$ to reach the 7% forward error correction (FEC) coding threshold of BER $= 3.8 \times 10^{-3}$. For $l = 2$, 3 and 4, larger SNRs are needed to reach BER $= 3.8\times10^{-3}$. Moreover, the recognition accuracy already exceeds 99% with $K = 1$ for an SNR of 11.4 dB, which can be further enhanced by increasing K. It can be concluded from Fig. 6 that accurate index recognition can be guaranteed at the minimum required SNR to reach the FEC coding threshold for communication.

IV. Conclusion

In this letter, we have proposed and experimentally demonstrated an intelligent index recognition scheme for OFDM-IM in UOWC systems. By adopting frequency-domain histograms as the recognition features, efficient intelligent index recognition can be realized through various machine learning or deep learning algorithms. The obtained experimental results show that k-NN can achieve better recognition performance than other recognition algorithms, and a larger SNR is required to perform satisfactory recognition for a higher constellation order in OFDM-IM. Compared with the existing likelihood-based and DNN-based index recognition schemes, the proposed scheme enjoys the advantages of low computational complexity and reduced training requirement.

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