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Intelligent automatic modulation recognition for OFDM with index modulation in underwater OWC systems

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Orthogonal frequency division multiplexing with index modulation (OFDM-IM) is shown to be an efficient modulation scheme for underwater optical wireless communication (UOWC) systems due to its high power efficiency and excellent flexibility. Differing from conventional OFDM, the modulation parameters of OFDM-IM consist of not only M -ary constellations but also subcarrier indices. In this Letter, we propose and demonstrate an intelligent automatic modulation recognition (AMR) scheme for OFDM-IM in UOWC systems by using Swin Transformer (Swin-T). Moreover, transfer learning with a hybrid training approach is further proposed to substantially enhance the AMR performance. Experimental results successfully demonstrate the feasibility and superiority of the proposed intelligent AMR scheme based on Swin-T with transfer learning and hybrid training in UOWC systems. More specifically, a recognition accuracy of 96% can be obtained by using Swin-T with transfer learning and hybrid training for a relatively small received signal-to-noise ratio (SNR) of 3.6 dB. © 2025 Optica Publishing Group. All rights, including for text and data mining (TDM), Artificial Intelligence (AI) training, and similar technologies, are reserved.

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Underwater optical wireless communication (UOWC) has been widely shown as a promising technology for practical underwater environments, which has attracted great attention in recent years [1]. Compared with traditional underwater acoustic and radio frequency communications, UOWC enjoys unique advantages such as large bandwidth, high data rate, low propagation latency, high security, small size, and low power consumption [2,3]. Nevertheless, practical UOWC systems generally suffer from two challenges: one is the limited usable bandwidth of commercial light sources such as light-emitting diodes (LEDs) and laser diodes (LDs), and the other is the highly dynamic and time-varying underwater channel condition affected by various factors such as water turbidity and turbulence [4].

So far, many techniques have been proposed for performance improvement of practical UOWC systems. Among which, orthogonal frequency division multiplexing with index modulation (OFDM-IM) has revealed great potential owing to its advantages of high power efficiency and excellent flexibility [5–7]. In OFDM-IM, the information bits are carried by both M -ary constellations and subcarrier indices, which is fundamentally different from that in conventional OFDM [8]. When OFDM-IM is applied in dynamic UOWC systems, both constellation (including constellation shape and order) and index (i.e., the exact number of activated subcarriers in each subblock) can be adaptively adjusted according to the change of the practical underwater channel conditions [9]. To efficiently perform OFDM-IM demodulation, both constellation and index information should be correctly known at the receiver side. Due to the time-varying characteristic of practical underwater channels, the considered constellation and index might change with time in OFDM-IM-based UOWC systems, which significantly increase the difficulty of OFDM-IM demodulation at the receiver side.

As a key enabling technique of adaptive modulation systems, automatic modulation recognition (AMR) is able to identify the detailed modulation parameters from the received signal and hence facilitate signal demodulation at the receiver side. Lately, several AMR schemes have been proposed for various OWC systems. In [10] and [11], AMR has been considered in visible-light-based OWC systems to realize classification among rectangular quadrature amplitude modulation (QAM) constellations with different orders. In [12], AMR has been used to classify time-domain waveforms including OFDM and pulse amplitude modulation (PAM). In [13], AMR has been applied in multiple-input multiple-output (MIMO) OWC systems to achieve open-set MIMO recognition. More specifically, an index recognition scheme has been further investigated for OFDM-IM-based UOWC systems in [14], where only index was recognized, while the recognition of constellation was ignored. The AMR for both index and constellation recognition based on a deep neural network (DNN) has been studied in [15], where two sub-networks were utilized to separately perform constellation and

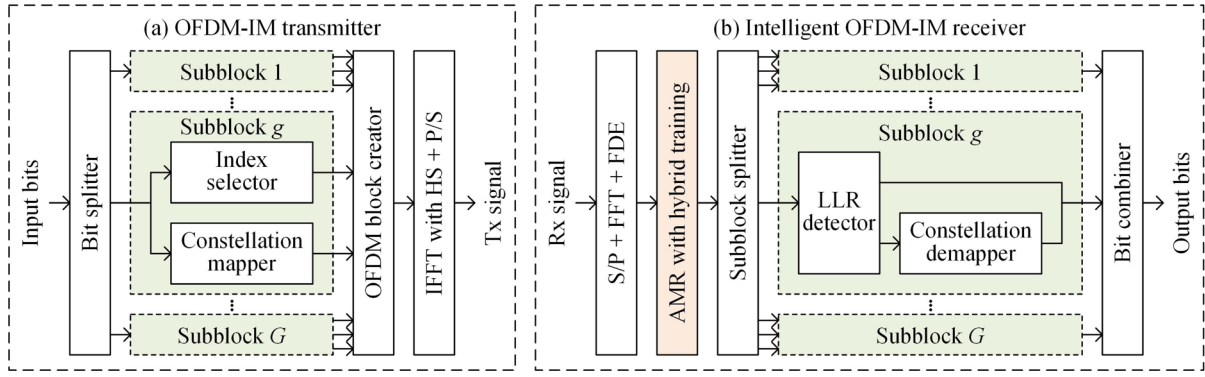


Fig. 1. Schematic diagram of the OFDM-IM system using intelligent AMR with hybrid training: (a) OFDM-IM transmitter and (b) intelligent OFDM-IM receiver.

index recognitions. To the best of our knowledge, AMR for joint constellation and index recognition in OFDM-IM-based UOWC systems has not yet been reported in the literature.

In this Letter, we propose and experimentally demonstrate a novel intelligent AMR scheme based on Swin Transformer (Swin-T) for OFDM-IM-based UOWC systems. To substantially enhance the recognition performance of the AMR scheme, transfer learning with a hybrid training approach is further proposed. Specifically, the hybrid training approach is realized by training the Swin-T with both experimental data and simulation data. Hardware UOWC experiments are conducted to evaluate and compare the performance of the proposed AMR scheme with other benchmark schemes.

Figure 1 depicts the schematic diagram of the OFDM-IM system using intelligent AMR with hybrid training. At the OFDM-IM transmitter, as shown in Fig. 1(a), the input bits are first divided into G streams via a bit splitter, and each bit stream is then sent into a subblock. In each subblock, the bit stream is further split into two parts, which are used to perform index selection and constellation mapping, respectively. For a subblock with length n , l out of n subcarriers can be selected to transmit constellation symbols, with $l \in \{1, 2, \dots, n\}$. Particularly, OFDM-IM becomes conventional OFDM when $l = n$ [16]. Subsequently, all the subblocks are combined together to create the OFDM block. After inverse fast Fourier transform (IFFT) with Hermitian symmetry (HS) and parallel-to-serial (P/S) conversion, the OFDM-IM signal is finally generated. At the intelligent OFDM-IM receiver, as shown in Fig. 1(b), the received signal is first converted to a parallel signal via serial-to-parallel (S/P) conversion, and then fast Fourier transform (FFT) and frequency domain equalization (FDE) are executed. In order to successfully perform OFDM-IM demodulation, intelligent AMR with hybrid training is further carried out to recognize both constellation and index jointly. The detailed principle of intelligent AMR with hybrid training will be discussed later. The overall OFDM block is split into G subblocks and log-likelihood ratio (LLR) detection is performed within each subblock to recover the index bits. The constellation symbols can be extracted accordingly for further constellation demapping, and the final output bits are obtained by combining the output bits of each subblock together. In this work, without loss of generality, we assume $n = 4$ with $l \in \{1, 2, 3, 4\}$, and a total of 6 basic constellations including binary phase shift keying (BPSK), quadrature phase shift keying (QPSK), 8PSK, 16PSK, 8-ary quadrature amplitude modulation (8QAM), and 16QAM are considered for

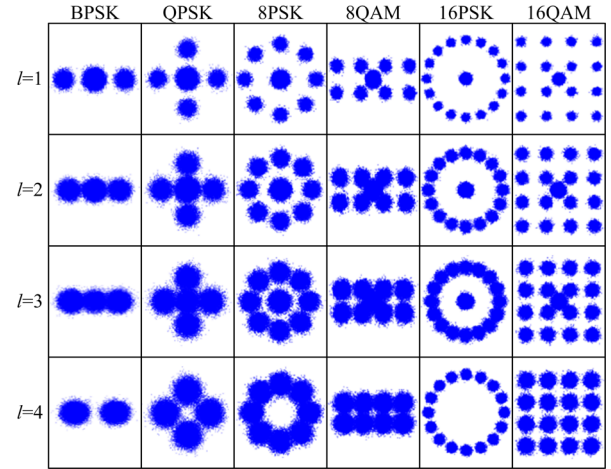


Fig. 2. Illustration of 24 OFDM-IM constellation images for 6 basic PSK/QAM constellations with different l values.

recognition. The 24 OFDM-IM constellation images for 6 basic PSK/QAM constellations with different l values are illustrated in Fig. 2.

The principle of the proposed intelligent AMR using Swin-T with transfer learning and hybrid training is shown in Fig. 3, where a tiny-size Swin-T model is adopted to balance the computational complexity and model performance. As the input of existing learning models generally takes the default format of RGB images, the Swin-T takes the RGB constellation images as the input, which are split into a series of non-overlapping patches, and each patch has a size of 4×4 . Since each pixel has three RGB channels, the dimension of each patch is given by $4 \times 4 \times 3$. The dimensions of the patch vectors are transformed into a predefined value using a linear embedding layer. This predefined value is the input dimension that the transformer can accept. The patches are processed through the Swin-T block in Stage 1. To capture multi-scale feature information, a hierarchical transformer structure is constructed. The size of the patches is continuously increased using a patch-merging operation. This allows access to multi-scale information through multiple stages. The patch-merging operation is similar to pooling, where neighboring patches are merged into one larger patch. This larger patch has an expanded receptive field and can capture multi-size features effectively [17]. After global average pooling and linear

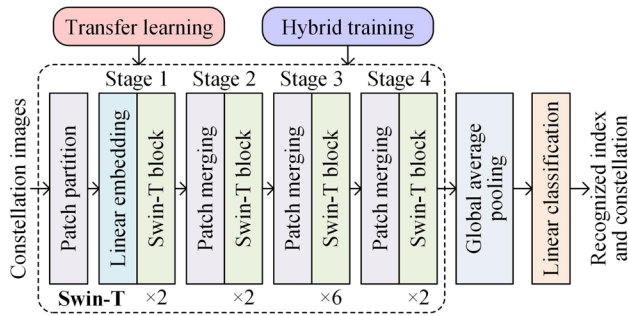


Fig. 3. Principle of intelligent AMR using Swin-T with transfer learning and hybrid training.

classification, the index and constellation associated with the input constellation images can be jointly recognized.

Considering that the successful training of Swin-T usually requires a large number of constellation image samples, we apply transfer learning in Swin-T to reduce the training requirement. More specifically, a pre-trained Swin-T based on the ImageNet dataset is used as a starting point for learning a new task; i.e., the pre-trained Swin-T is further fine-tuned based on the OFDM-IM constellation image dataset [18]. Since the constellation images have similar shallow and deep features as that of the images included in the ImageNet dataset, the weights and other parameters of the pre-trained Swin-T only need to be moderately updated to converge; i.e., it needs much less data to fine-tune the pre-trained Swin-T to obtain the features that distinguish the OFDM-IM constellation dataset and then achieve satisfactory recognition performance. Moreover, a hybrid training approach is also proposed to further reduce the training requirement, in which the constellation image samples used for training are collected from both real-world UOWC systems and computer simulations. Particularly, since the noise in real-world UOWC systems can be reasonably assumed to be an additive white Gaussian noise (AWGN), it is feasible to generate constellation image samples for training through computer simulations by adopting an AWGN channel with the practically estimated received signal-to-noise ratio (SNR). Hence, the training data consists of both real-world measured data and computer simulated data, enabling hybrid training for the Swin-T. It should be noted that the AWGN channel model adopted in the simulation can be replaced with a more practical channel model according to the practical channel conditions of the UOWC system.

To evaluate and compare the performance of the proposed intelligent AMR using Swin-T with transfer learning and hybrid training with other benchmark schemes in OFDM-IM-based UOWC systems, hardware experiments are conducted in a lab environment. The experimental setup of the UOWC system is depicted in Fig. 4, where the transmitted signal is first generated offline by MATLAB and then loaded to an arbitrary waveform generator (AWG, Tektronix AFG31102) with a sampling rate of 250 MSa/s. Subsequently, the AWG output signal is used to drive a commercially available optical transmitter module (HCCLS2021MOD01-Tx), which is powered by a 12 V DC bias voltage. The emitted blue light passes through a 1 m water tank filled with tap water, and a corresponding optical receiver module (HCCLS2021MOD01-Rx) is adopted to detect the light signal, which is also powered by a 12 V DC bias voltage. For more details about the Tx/Rx modules, please refer to our previous work [19]. The detected signal is recorded by a digital storage

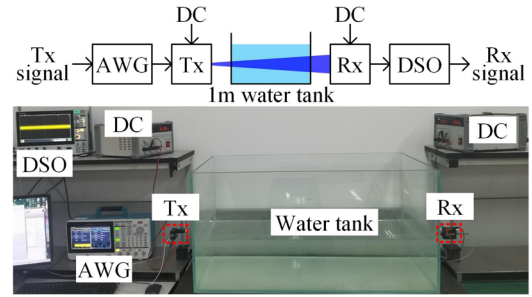


Fig. 4. Experimental setup of the UOWC system.

Table 1. Experimental Parameters

Parameter	Value
IFFT/FFT size	256
Number of data subcarriers	64
Subblock length	4
Number of activated subcarriers in subblock	1, 2, 3, 4
Swin-T patch dimension	$4 \times 4 \times 3$
AWG sampling rate	250 MSa/s
DSO sampling rate	1.25 GSa/s
Effective signal bandwidth	62.5 MHz

oscilloscope (DSO, Tektronix MDO32) with a sampling rate of 1.25 GSa/s, and the obtained data are further processed offline using MATLAB. In OFDM-IM modulation/demodulation, the IFFT/FFT size is 256, and the number of data subcarriers is 64. Hence, the effective bandwidth of the OFDM-IM signal is 62.5 MHz. The key experimental parameters can be found in Table 1.

Moreover, for a given received SNR value, a total of 240 constellation image samples are collected from the experimental OFDM-IM-based UOWC system to perform recognition of 24 OFDM-IM constellations, where 192 samples are used for training, while 48 samples are used for testing. To perform hybrid training, more constellation image samples are generated via computer simulations. The proposed intelligent AMR using Swin-T with transfer learning and hybrid training is implemented in PyTorch with an NVIDIA GeForce RTX 3090 GPU. In addition, the benchmark schemes include DNN, convolutional neural network (CNN), and Vision Transformer (ViT).

Figure 5 shows the recognition accuracy versus received SNR for different schemes. As we can see, the recognition performance using traditional DNN and CNN is relatively poor, with an accuracy of less than 60% for a relatively large received SNR of 11.6 dB. Moreover, the recognition performance can be greatly improved for relatively large received SNR values when using ViT and Swin-T. Specifically, for a relatively large received SNR of 11.6 dB, the accuracy is increased from 58% to 100% when CNN is replaced by ViT or Swin-T. Nevertheless, the overall recognition performance using ViT and Swin-T is still not satisfactory at low-SNR values. By applying transfer learning in Swin-T, the low-SNR recognition performance can be moderately enhanced. Taking SNR = 3.6 dB as an example, the accuracy is increased from 44% to 67% after the utilization of transfer learning based on the ImageNet dataset. It can be observed from Fig. 5 that the best recognition performance is achieved by Swin-T with transfer learning and hybrid training, where the hybrid training ratio (i.e., the ratio of the number of experimental samples and the number of the simulation samples)

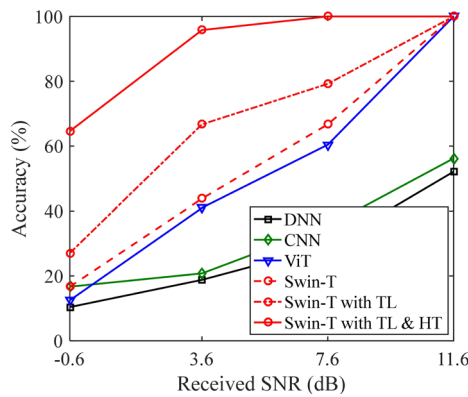


Fig. 5. Recognition accuracy versus received SNR for different schemes. TL, transfer learning; HT, hybrid training.

is assumed to be 1:10. With the aid of sufficient simulation samples for hybrid training, the overall recognition performance is significantly improved especially in the low-SNR region. Particularly, the accuracy is increased from 67% to 96% at SNR = 3.6 dB after introducing hybrid training, and an accuracy above 60% can also be achieved with a received SNR as low as -0.6 dB. Figure 5 clearly demonstrates the advantages of using transfer learning and hybrid training to enhance the overall AMR performance based on Swin-T with a relatively small number of constellation image samples collected from the practical OFDM-IM-based UOWC system.

Figure 6 shows the recognition accuracy versus hybrid training ratio for Swin-T with transfer learning and hybrid training with different received SNRs. It can be seen that the lowest recognition accuracy is achieved when the hybrid training ratio is 1:0; i.e., only experimental data are used for training, for relatively small received SNR values. Moreover, the recognition accuracy first gradually increases with the decrease of the hybrid training ratio and then becomes stable when the hybrid training ratio is reduced to 1:5 for the received SNR values of -0.6, 3.6 and 7.6 dB. Specifically, an accuracy of 100% can be obtained when the hybrid training ratio reaches 1:5 for a received SNR of 7.6 dB, while the obtained accuracies are 64% and 96% when the hybrid training ratio reaches 1:5 for received SNRs of 3.6 and -0.6 dB, respectively. Therefore, the use of hybrid training with a proper hybrid training ratio can result in substantially improved AMR performance compared with the case without introducing simulation data for hybrid training.

In this Letter, we have proposed and experimentally demonstrated a Swin-T-based intelligent AMR scheme for OFDM-IM in UOWC systems, which can jointly recognize both constellation and index of the received OFDM-IM signals. To reduce the training requirement of Swin-T and hence substantially enhance the AMR performance, two techniques have been further proposed including transfer learning and hybrid training. By using a pre-trained Swin-T with the ImageNet dataset as a starting point, the Swin-T can be efficiently trained based on the OFDM-IM constellation image dataset. Moreover, computer simulated constellation image samples can be introduced to enrich the experimental constellation image dataset, enabling hybrid training for Swin-T-based intelligent AMR scheme in OFDM-IM-based UOWC systems. The obtained experimental results show that intelligent AMR can be efficiently realized by

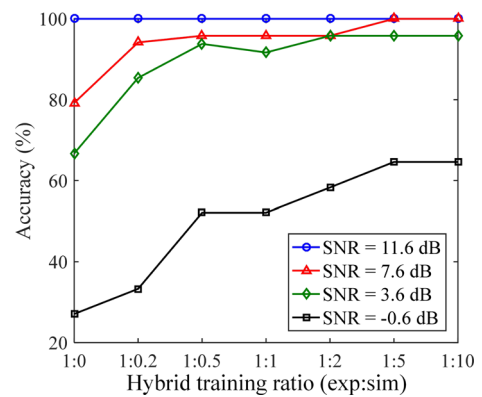


Fig. 6. Recognition accuracy versus hybrid training ratio for Swin-T with transfer learning and hybrid training with different received SNRs. exp, experimental; sim, simulation.

utilizing Swin-T with transfer learning and hybrid training for OFDM-IM in UOWC systems.

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Data availability. Data underlying the results presented in this Letter are not publicly available at this time but may be obtained from the authors upon reasonable request.

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