Research Article

Underwater Modulation Classification Using Discrete Wavelet Transform and Genetic Algorithm

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ABSTRACT

Underwater wireless optical communication systems face significant challenges due to the heterogeneous nature of the underwater environment and the attenuation of optical signals caused by absorption and scattering. These effects restrict the data transfer capacity and transmission distance, resulting in communication errors. Different modulation techniques are used to minimize the effects of these parameters. Automatic modulation classification plays a critical role in terms of effective management of spectrum resources. In this study, underwater wireless optical communication channels are modulated with different modulation techniques, and the signals are transformed into the discrete wavelet space, resulting in approximation and detail coefficients that are used as feature vectors for training machine learning algorithms. In addition, optimized classification features are determined for different signal-to-noise ratios and different transmission distances using the genetic algorithm. The results show that the approximation and detail coefficient energies provide higher classification performance in the classification of modulated signals according to statistical features such as mean, variance, and standard deviation. According to simulation results, an average classification accuracy of 82% has been obtained using the proposed discrete wavelet transform and genetic algorithm-based technique, which demonstrates high classification accuracy for noisy underwater channels.

1. Introduction

Underwater wireless communication (UWC) has become an urgent need for the effective use of underwater resources [1]. Underwater area security and surveillance, exploration of oil fields, monitoring underwater environment and pollution are the leading ones [2]. Acoustic and radio signals and optical communication technologies are the main techniques used for underwater wireless communication [3]. Systems which use acoustic signals are effective in terms of being resistant to the heterogeneous structure of the underwater habitat and suitable for communication over long distances [3]. On the other hand, these systems cannot come with an effective solution to today's communication needs due to their narrow bandwidth, low data transmission speed and high energy requirements[4]. Underwater electromagnetic (EM) wave propagation is more resistant to polluted water conditions and the heterogeneous structure of the underwater habitat than both acoustic and optical signals. In addition, data transmission systems based on EM signals are not adversely affected by ambient noise and underwater climate conditions compared to the mentioned methods [5]. However, the propagation of EM waves in the channel requires the elimination of specific difficult conditions since the relative permittivity and electrical conductivity of water are higher than air [6]. As an alternative to the EM and acoustic systems, underwater wireless optical communication (UWOC) attracts attention in terms of providing high data transmission speed, sufficient bandwidth, and being low-cost system [7]. In addition, UWOC systems have significant advantages including low latency and immunity to electromagnetic interference. UWOC is performed using the visible light band of the spectrum ranging from 380 nm to 750 nm.

Coastal and ocean waters have diverse intrinsic physio-chemical biological environments that cause various propagation phenomena [8]. Therefore, in UWOC communication, the absorption of light by water itself, and scattering of light by suspended particles and plankton are two important elements affecting signal propagation [8]. The optical properties arising from the nature of light include the absorption and scattering coefficients, the attenuation coefficient—which is defined as the sum of these two coefficients—and the volumetric scattering function [9]. The absorption and scattering effects lead to a decrease in the number of photons received by the end-devices, causing inter-symbol interference (ISI) and energy loss [10].

In this study, 5 modulation signals having different characteristics are generated considering an underwater channel model based on Beer-Lambert law. As a novel approach to underwater modulation classification problem, Discrete Wavelet Transform (DWT) and Genetic Algorithm (GA) have

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been combined where DWT has been utilized for feature extraction and Genetic Algorithm (GA) has been used for optimized feature selection. The classification is performed via K Nearest Neighborhood Algorithm using the optimized features. We achieved 82% average classification accuracy across five modulation techniques (OOK, PPM, QAM, QPSK, SIM) under challenging underwater conditions.

2. Materials and Method

2.1. Proposed Scheme

The two important processes that cause attenuation are absorption and scattering. In UWOC, the attenuation coefficient, expressed as the sum of the absorption and scattering coefficients, is formulated as follows [11]:

$$c(\lambda) = a(\lambda) + b(\lambda) \tag{1}$$

Here, the terms a(λ), b(λ), and c(λ) represent the absorption, scattering, and attenuation coefficients for the λ wavelength, respectively. Underwater optical propagation channel does not exhibit steady channel-characteristics due to pollution, salinity, temperature, concentration of suspended particles, and heterogeneous distribution of sunlight. As a result, it causes the absorption and scattering coefficients to change depending on the properties of the water. In the literature, for simulation of underwater optical communication systems, the channels are divided into 4 classes, namely sea, clear ocean, coastal ocean, and turbid harbor water [12]. The absorption and scattering coefficients for different water types are listed in Table 1 [13].

Table 1. Absorption, scattering, and attenuation coefficients for the 4 categories of water.

Water	$\boldsymbol{a(\lambda)\ (m^{-1})}$	$\boldsymbol{b(\lambda)\ (m^{-1})}$	$\boldsymbol{c(\lambda)\ (m^{-1})}$
Pure sea	0.053	0.003	0.056
Clean ocean	0.069	0.08	0.151
Coastal ocean	0.088	0.216	0.305
Turbit harbor	0.295	1.875	2.170

2.2. Underwater Wireless Optical Communication Channel

There are two types of optical link configurations in UWOC. The first one is the line of sight (LOS) configuration where it is assumed that there is no obstacle between the receiver and the transmitter, i.e. they are directly in line of sight [14]. The other configuration is given as non-line of sight (NLOS), where the line of sight between the receiver and the transmitter is provided indirectly, which represents the real-world conditions more accurately [15]. Underwater optical link configurations are shown in Figure 1.

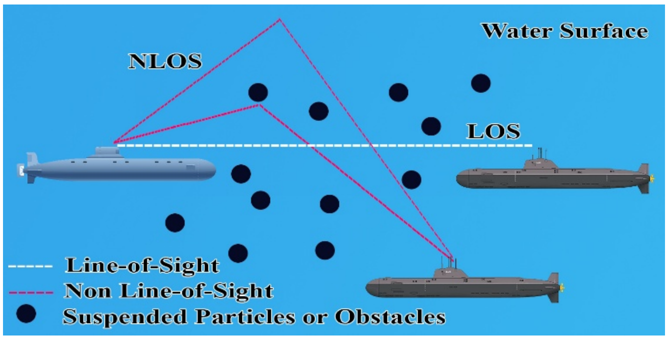

Fig. 1. Underwater Optical Link Configurations

Since the purpose of this study is modulation classification, the link type parameters remained in a limited range. Therefore, Beer-Lambert law is utilized where the LOS is a channel attenuation model. The Beer-Lambert law calculates the loss of light power during underwater propagation. In addition, it ignores the negative effects of scattering, turbulence, or communication without direct line of sight caused by the underwater natural environment. According to the Beer-Lambert law, the power of light travelling a distance z from the transmitter to the receiver is computed according to following formula[11] :

$$I = I_0 e^{-c(\lambda)z} \tag{2}$$

Here, I is the output power of the light (W); I_0 is the input power of the light (W); c(λ) is the total attenuation coefficient due to the underwater environment m^{-1} and z is the distance between the receiver and the transmitter (m).

2.3. Classification of Modulation Techniques

The automatic recognition of modulation signals is crucial for wireless communication systems that use different modulation techniques [15]. Classification of modulation techniques is an important system parameter in both non-cooperative military and civilian applications [16]. In this study, 5 modulation techniques frequently used in UWOC communication systems have been considered, and a performance evaluation has been made based on the proposed system. On-off keying (OOK), which is frequently preferred due to its easy application in UWOC systems, and pulse position modulation (PPM) which is a type of pulse modulation based on changing the positions of pulses within a fixed period [17], are two of the modulation techniques simulated in this study. Quadrature amplitude modulation (QAM), the technique that carries information using both amplitude and phase information, has also been used. As another modulation technique, quadrature phase shift keying (QPSK) has been preferred [18]. Finally, the sub-carrier intensity modulation (SIM) technique, which changes the optical carrier density with a subcarrier signal, has been implemented [19]. In this study, 100 signals, each consisting of 64 bits, have been subjected to modulation using the aforementioned modulation schemes. In the modulation process, for each modulation type, the bit rate has been determined as 1000 bps, the bit duration as 0.001 seconds, the sampling frequency as 20 kHz, the number of samples per bit as 20, the carrier wavelength of the signal used as 532 nm (green light) and the output power of the optical signal as 1 mW. Gaussian noise has been added to the modulated signals, and they have been passed through the underwater wireless optical channel by being subjected to attenuation under the Beer-Lambert law. The simulations have been carried out for various signal-to-noise ratio (SNR) levels and for various ranges of distances between the receiver and transmitter.

2.4. Automatic Classification of Modulation Techniques

2.4.1. Feature Selection

Feature selection is frequently used in machine learning and data classification. Feature selection can be defined as determining the most accurate representation of the most distinctive features of the data to be classified [20]. Before classification, DWT has been used to transform the signal into coefficients in Fourier space (approximation and detail) according to different frequency ranges [21]. Approximation coefficients decompose the signal into low-frequency components that represent the general trend of the data, while detail coefficients decompose the signal into high-frequency components highlighting fine details and abrupt changes. In this study, Haar, Daubechies (db2), Biorthogonal (Bior3.3), and Coiflet (Coif2) wavelet functions have been chosen based on their distinct properties and proven effectiveness in signal classification tasks [22, 23]. Haar wavelet, similar to a step function and is a discontinuous signal [24], is applied as a wavelet. Another wavelet, the Daubechies (db2), is a compact-supported, orthogonal wavelet used for the DWT and a multi-resolution transform that represents the signal at different resolution levels [25]. Bior (Biorthogonal 3.3) wavelets belong to the biorthogonal wavelet family and are analyzed and synthesized using different filters in both decomposition and reconstruction of the signals. The Bior3.3 is frequently preferred for data compression, edge detection and medical signal processing due to its symmetric and biorthogonal structure [26]. Coiflets wavelet family includes orthogonal wavelets developed by Daubechies and optimized to provide higher moment conditions. The Coif2 wavelet is the second-order member of the Coiflets family and is preferred due to its symmetric structure and high accuracy time-frequency resolution [27].

Three-level DWTs have been carried out for the four wavelet types mentioned above. All the approximation and detail coefficients have been obtained for each level. The mean, variance, and energy parameters of both approximation and detail coefficients have been computed and they have been used as training data for machine learning process. As a result, 18 features have been extracted separately for each wavelet function. The details of the extracted features are given in Table 2.

Table 2. The wavelet features of data set: Approximation (Ap.); Detail (De.)

Level	**Mean**		**Variance**		**Energy**	
1	Ap.	De.	Ap.	De.	Ap.	De.
2	Ap.	De.	Ap.	De.	Ap.	De.
3	Ap.	De.	Ap.	De.	Ap.	De.

2.4.2. Feature Selection using Genetic Algorithm

Genetic algorithms try to solve a population of existing solutions using evolutionary processes such as natural selection, crossover, mutation, and elitism to find the desired optimum solution for a problem [28]. The feature selection algorithm aims to discover a subset of the candidate set given at the input and to make a finer classification with fewer features [29]. Feature selection will reduce the number of features needed for machine learning algorithms and also it will reduce the cost [30]. In this study, the parameters of the genetic algorithm used for feature selection are determined as follows: population size is 50, number of generations is 100, crossover rate is 0.9, mutation rate is 0.1, the size of the tournament selection used as the selection mechanism is 4 and the number of individuals to be kept as elite is 5. In addition, the ratio of test data used in the genetic algorithm is 0.2.

2.4.3. Classification

In the proposed system model, 3-level transformations of modulated signals have been performed using Haar, Daubechies (db2), Bior (Biorthogonal 3.3), and Coiflets (Coif2) wavelet functions. For each wavelet, 3 approximation and 3 detail coefficients have been extracted at each level. All coefficients have mean, variance, and energy parameters, and thus, a total of 18 features have been extracted. In this study, the genetic algorithm has been utilized as a feature selection tool. The task of the genetic algorithm is to reduce the features in a way that the best classification among different features can be made with the least number of features if it is possible. In the genetic algorithm, the individual is the selected set of features, and the fitness score of the individual is the accuracy rate of the classification made with the K-Nearest Neighbor (KNN) classification algorithm. The flow diagram of the proposed system is given in Figure 2.

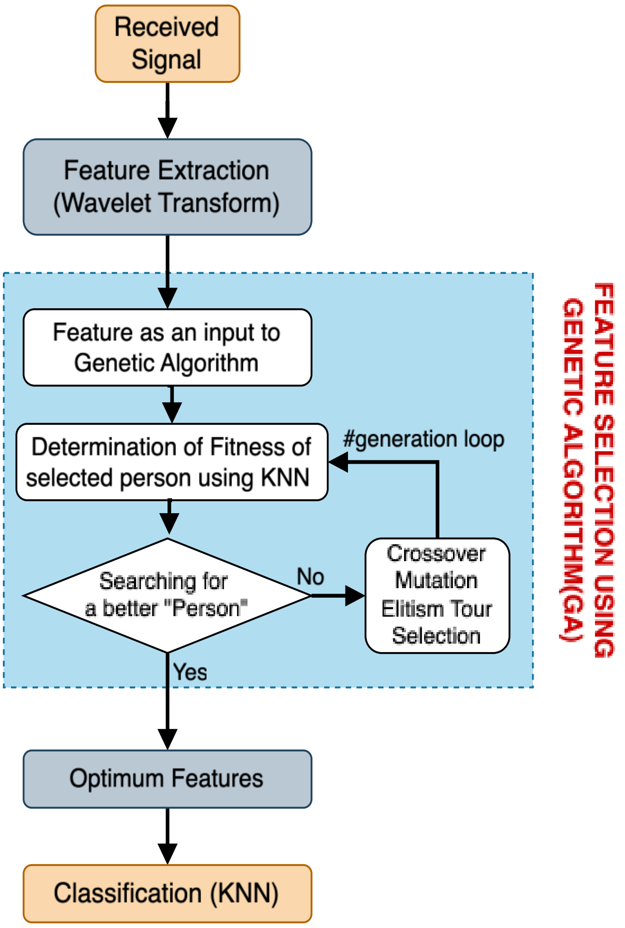

Fig. 2. Flowchart of the proposed system

3. Results and Discussion

The proposed system has been simulated for various parameter values which were obtained considering different water characteristics. Table 3 shows a general result of the proposed system simulated on different SNR values of the signals; where M is the distance between the receiver and transmitter, W is the class of wavelet utilized for feature extraction, and D is the classification accuracy.

Table 3. Selected Features

SNR	M	W	D	Selected Features
-10	10	Bior 3.3	0.92	2,4,8,10,15,18
-10	10	Haar	0.89	3,5,6,8,9,13,14
-10	10	Db2	0.9	8,11,13,14,18
-10	10	Coif 2	0.93	1,5,7,8,9,12,13
-10	20	Bior 3.3	0.94	2,5,6,9,10,16,17
-10	20	Haar	0.88	2,9,10,11,12,14,16,17,18
-10	20	Db2	0.87	1,2,5,6,7,8,11,12,13
-10	20	Coif 2	0.90	2,5,7,14,18
-10	30	Bior 3.3	0.88	3,4,5,6,7,8,9,12,13,15,17,18
-10	30	Haar	0.86	2,3,5,7,8,9,12,14,15,16,17
-10	30	Db2	0.85	3,6,8,11,13,18
-10	30	Coif2	0.86	1,2,4,5,6,7,9,10,14,15,17,18
-10	40	Bior 3.3	0.86	4,6,8,9,10,11,12,17
-10	40	Haar	0.89	1,3,4,6,7,8,9,11,12,13,14,5,16
-10	40	Db2	0.91	2,5,6,8,9,11,12,15,16,17
-10	40	Coif2	0.89	2,5,6,8,10,11,16
-10	50	Bior 3.3	0.90	3,6,8,11,12,13,15,18
-10	50	Haar	0.88	1,7,8,13,14,15,17,18
-10	50	Db2	0.94	2,5,6,7,8,12,13,14,16
-10	50	Coif2	0.93	1,3,4,7,11,12,14,15,18
-5	10	Bior 3.3	0.95	5,6,7
-5	10	Haar	0.91	1,2,3,6,10,11,14,15
-5	10	Db2	0.94	3,5,7,8,10,12,17
-5	10	Coif 2	0.87	2,3,7,8,9,10,15
-5	20	Bior 3.3	0.86	2,5,9,10,11,12,15,16
-5	20	Haar	0.87	1,2,5,6,8,10,11,12,13,15
-5	20	Db2	0.94	1,3,5,6,10,11,14,16
-5	20	Coif 2	0.86	2,3,4,5,6,9,10,15,16,17
-5	30	Bior 3.3	0.87	1,2,6,9,10,11,13,14
-5	30	Haar	0.89	1,7,9,10,12,13,17,18
-5	30	Db2	0.91	2,3,4,5,7,11,12,17,18
-5	30	Coif2	0.89	2,5,6,7,9,10,11,12,15
-5	40	Bior 3.3	0.91	1,6,7,10,11,13,14,17,18
-5	40	Haar	0.91	7,10,11,18
-5	40	Db2	0.91	1,7,8,9,10,11,16,17,18
-5	40	Coif2	0.86	1,3,5,7,8,10,11,12,15,18
-5	50	Bior 3.3	0.81	6,9,11,14,15
-5	50	Haar	0.88	4,6,9,11,12,14,15,17,18
-5	50	Db2	0.8	3,4,6,10,11,13,14,15,16,17
-5	50	Coif2	0.8	4,5,7,8,14,17
0	10	Bior 3.3	0.95	1,3,8,10,11,12,13,17
0	10	Haar	0.9	2,3,4,14,15,16,18
0	10	Db2	0.94	3,4,7,8,9,15,17,18
0	10	Coif 2	0.96	1,3,4,6,8,9,10,11,12,13
0	20	Bior 3.3	0.95	1,2,4,6,7,9,10,17,18
0	20	Haar	0.89	1,3,4,5,8,11,13,14,15,17,18
0	20	Db2	0.9	3,4,6,9,10,12,15,16,18
0	20	Coif 2	0.92	1,3,6,7,8,9,10,11,12,16,18
0	30	Bior 3.3	0.89	4,5,6,8,9,11,13,14,15
0	30	Haar	0.9	3,4,8,12,14,15,17
0	30	Db2	0.92	3,6,8,10,13,17,18
0	30	Coif2	0.93	2,5,7,9,11,14,15,18
0	40	Bior 3.3	0.89	1,2,4,14,15
0	40	Haar	0.87	1,2,3,4,6,7,9,11,14,15,16,18
0	40	Db2	0.89	2,5,6,7,9,12,13,15
0	40	Coif2	0.9	1,3,6,11,12,13,14,17,18
0	50	Bior 3.3	0.9	1,3,5,9,11,12,14,15
0	50	Haar	0.87	2,3,11,12,13,15,18
0	50	Db2	0.87	1,2,5,6,7,8,10,12,13,14
0	50	Coif2	0.87	1,5,7,9,10,11,12,16,18
10	10	Bior 3.3	0.92	1,2,3,9,10,11,13,14,15
10	10	Haar	0.91	1,3,4,5,7,8,9,13,14,17,18
10	10	Db2	0.94	2,4,12,14,15,16
10	10	Coif 2	0.95	1,3,5,7,8,9,12,15,17
10	20	Bior 3.3	0.92	1,2,3,4,6,8,9,10,12,15
10	20	Haar	0.91	1,2,3,4,7,8,9,12,
10	20	Db2	0.89	1,5,6,9,12,14,15,16,17,18
10	20	Coif 2	0.93	7,11,14,15,17
10	30	Bior 3.3	0.93	1,3,5,6,7,9,13,15,17,18
10	30	Haar	0.93	1,2,7,10,11,12,17
10	30	Db2	0.92	6,7,8,14,15,17
10	30	Coif2	0.93	6,9,12,13
10	40	Bior 3.3	0.91	2,6,8,9,11,14,15,17,18
10	40	Haar	0.90	3,5,6,10,11,15
10	40	Db2	0.9	1,3,4,5,7,12,13,14,17,18
10	40	Coif2	0.92	2,4,5,6,13,14
10	50	Bior 3.3	0.93	1,2,3,7,12,15,18
10	50	Haar	0.88	1,2,3,9,10,11,13
10	50	Db2	0.91	2,3,6,8,9,14,15
10	50	Coif2	0.9	2,3,4,6,10,15,17

According to Table 3, the classification accuracy remains in a limited range at low SNR (-10 dB, -5 dB) levels as expected. It has been observed that Coif2 and Bior 3.3 wavelets generally provide higher accuracy at low SNR values. Although the Haar wavelet provides lower accuracy at low SNR levels, it has been observed that it performs well in some cases with certain features. The Bior 3.3 wavelet generally has stable performance and can give the best results at low SNR levels. It is observed that the features of level 2 and level 3 are more selected by the genetic algorithm. According to the table, the 5 most selected features are given as energy of approximation coefficients at level 3 (43 times), energy of detail coefficients at level 1 (43 times), energy of approximation coefficients at level 2 (41 times), variance of detail coefficients at level 2 (40 times), and energy of approximation coefficients at level 1 (40 times), respectively. These results show that 4 of the 5 most selected features are energy parameters.

The best 5 features have been used separately according to the four wavelet types and the classification has been made based on the K Nearest Neighbor Classification algorithm (k=10) using only K-fold cross-validation (k=10). The results are given in Table 3 through Table 6 for each wavelet. The modulated signals are assumed to be at a distance of 20 m to receiver and have an SNR level of -5 dB. When the confusion matrices for the best 5 features are evaluated, it has been observed that the classification error is mainly caused by QAM and QPSK classes throughout 5 modulation techniques.

The results demonstrate that all the considered wavelets achieve high classification performance for OOK, PPM, and SIM signals. However, performance deteriorates significantly for QAM and QPSK signals due to their inherent modulation similarities, which complicate discrimination. QAM and QPSK signals present more significant classification results, as all the wavelets perform well for the simpler modulation schemes (OOK, PPM, SIM). The Coif2 wavelet yields classification accuracies of 0.8 for QAM and 0.4 for QPSK. The Haar wavelet performs poorly, with an average accuracy of 80% ranking it among the least effective options. While the Db2 and Bior3.3 wavelets exhibit comparable performance, Db2 slightly outperforms Haar in terms of classification accuracy of QAM signals.

The proposed classification scheme achieves an average classification accuracy of 82% for overall wavelets despite the high complexity of the five-class problem. While DWT coefficients exhibit excellent classification performance for modulation schemes with distinct characteristics (OOK, PPM, and SIM), the performance degrades for modulation types sharing similar properties such as QAM and QPSK. At this point, it is worth noting that the genetic algorithm consistently identifies energy parameters as the most discriminative features across all considered wavelets.

		True Class				
		OOK	QAM	QPSK	PPM	SIM
Predicated Class	OOK	10	0	0	0	0
	QAM	0	8	6	0	0
	QPSK	0	2	4	0	0
	PPM	0	0	0	10	0
	SIM	0	0	0	0	10

Fig.3. Coif 2 Transform Confusion Matrix, Accuracy: %84

		True Class				
		OOK	QAM	QPSK	PPM	SIM
Predicated Class	OOK	10	0	0	0	0
	QAM	0	4	4	0	0
	QPSK	0	6	6	0	0
	PPM	0	0	0	10	0
	SIM	0	0	0	0	10

Fig.4. Haar Transform Confusion Matrix, Accuracy: %80

		True Class				
		OOK	QAM	QPSK	PPM	SIM
Predicated Class	OOK	10	0	0	0	0
	QAM	0	6	5	0	0
	QPSK	0	4	5	0	0
	PPM	0	0	0	10	0
	SIM	0	0	0	0	10

Fig.5. Db 2 Transform Confusion Matrix, Accuracy: %82

Predicated Class \ True Class	OOK	QAM	QPSK	PPM	SIM
OOK	10	0	0	0	0
QAM	0	5	5	0	0
QPSK	0	5	5	0	0
PPM	0	0	0	10	0
SIM	0	0	0	0	10

Fig.6. Bior3.3 Transform Confusion Matrix, Accuracy: %82

4. Conclusion

In this study, it is targeted to classify modulation signals used in underwater communications considering five different modulation techniques. A three-level discrete wavelet transform has been considered for feature extraction and an 18-dimensional feature vector has been obtained by computing the mean, variance, and energy of the detail and approximation coefficients at each level. In addition, a genetic algorithm has been utilized to determine the most significant features. The five most discriminative features have been selected, and an average accuracy of 82% has been achieved using the K-nearest neighbors algorithm considering four primary wavelets (Coif2, Haar, Db2, and Bior3.3). The presented work in this study can support underwater robots for exploring the seabed, sensors for real-time pollution tracking, and military systems needing secure, fast communication. In future studies, the use of advanced classifiers such as SVM or CNN may be considered to further improve the classification of complex modulation types. Additionally, designing adaptive systems that can dynamically adjust modulation based on channel feedback can make it possible to achieve high-performance modulation classification over larger deployment areas.

Authorship Contributions

Authors equally contributed to this work.

Declaration of conflicting interests

The authors declare no competing interests.

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Ethics

There are no ethical issues with the publication of this manuscript.

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