Machine Learning for Underwater Acoustic Communications

Lihuan Huang, Yue Wang, Qunfei Zhang, Jing Han, Weijie Tan, and Zhi Tian

Abstract

Energy-efficient and link-reliable underwater acoustic communication (UAC) systems are of vital importance to both marine scientific research and oceanic resource exploration. However, owing to the unique characteristics of marine environments, underwater acoustic (UWA) propagation experiences arguably the harshest wireless channels in nature. As a result, traditional model-based approaches to communication system design and implementation may no longer be effective or reliable for UAC systems. In this article, we resort to machine learning (ML) techniques to empower UAC with intelligence capabilities, which capitalize on the potential of ML in progressively improving system performance through task-oriented learning from data. We first briefly overview the literature of both UAC and ML. Then, we illustrate promising ML-based solutions for UAC by highlighting one specific niche application of adaptive modulation and coding (AMC). Lastly, we discuss other key open issues and research opportunities layer-by-layer, with focus on providing a concise taxonomy of ML algorithms relevant to UAC networks.

Introduction

Ocean, which covers two-thirds of our planet, provides a huge amount of under-utilized resources. Nowadays, marine exploitation has attracted growing attention, thanks to the rapid development of underwater acoustic (UWA) technologies. Among them, underwater acoustic communication (UAC) systems and networks have found broad applications, such as environmental monitoring, offshore exploration, disaster detection and early warning, as well as national security and defense. Therein, how to enhance the reliability and efficiency of UAC systems is key to the exploration of oceanic resources in harsh aquatic environments [1].

Traditional UAC research generally assumes some specific channel conditions or even ideal environments that match certain well-understood channel models for air-based transmission medium. As such, mature designs for terrestrial wireless systems can be adopted, which simplifies the design of UACs. Unfortunately, these designs derived from simple and ideal channel conditions may not work well in practice. The very first and foremost obstacle turns out to be the lack of a set of general channel models that accurately describe diverse practical scenarios, which limits the applicability of traditional model-based communication techniques.

Specifically, in contrast to terrestrial wireless communications, signals in underwater transmission propagate in the form of acoustic waves rather than the electromagnetic counterparts, since almost all electromagnetic frequencies are absorbed and dispersed by water. Table 1 summarizes and compares the key characteristics between these two different media. Noticeably, UACs suffer from much more complex channel distortion and interference than the counterpart of terrestrial radio systems. All these adverse characteristics pose serious performance-degrading factors to UAC systems in practice.

In UAC research, there are several mathematical modeling techniques for UWA wave propagation, including the parabolic approximation model, the normal model and the ray-theoretic model, and so on. Among them, the ray-theoretic model is most widely used due to its interpretability and simplicity. It assumes that sound propagates along a huge amount of rays generated from the source point (i.e., transmitter), while the receiving signal is the total sound energy of all arriving rays. Therein, following Snell's law, acoustic rays always bend toward the region with lower propagation velocity, which depends on the temperature, salinity and depth that vary with time and location [2]. As such, certain small changes of these environmental parameters in UAC may result in drastic variation of sound velocity, which causes refraction-induced abnormal acoustic ray paths. Such fast dynamics of UWA environments give rise to a highly irregular sound speed profile (SSP), which leads to highly complex UWA propagation. Such complexity makes it quite challenging to construct accurate and general UWA channel models in an affordable manner.

Meanwhile, inspired by the success of stochastic channel modeling techniques in terrestrial and satellite communications, some UAC researchers have attempted to make statistical assumptions on the individual paths of a given UWA channel impulse response, aiming to generate the required channel parameters from their probability distributions in a stochastic manner. Unfortunately, the fast dynamic changes in an aquatic environment lead to complex time-space-frequency variations in UWA channels. Thus, accurate statistical models for specific UWA channels are still unavailable, even though a vast number of measurements on

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Characteristic	Electromagnetic waves	Underwater acoustic waves
Medium dependence	Propagate regardless of medium, even in vacuum	Must rely on medium vibration
Propagation uniformity	Generally along a straight line, at a stable speed	Along a curve, with speed greatly affected by temperature
Absorption loss under water	3dB/m@10kHz	1.1dB/km@10kHz
Speed in the air	3 × 108 m/s	340m/s
Speed under water	2.25 × 108m/s	1490m/s
Typical frequency and wavelength	GSM – frequency: 900MHz, wavelength: 0.33m	Sonar – frequency: 5kHz, wavelength: 0.3m
Communication latency	Small	Large
Multipath delay	Small multipath delay	Large delay (> 10ms), across dozens of symbols
Doppler	Small scaling factor ($\leq 10^{-5}$)	Large scaling factor (10^{-2})
Variation in time and space	Change of communication scenarios and variation in short-wave ionospheric reflection	Rapid changes of waves and periodic changes of sea water

TABLE 1. Comparison of electromagnetic waves and UWA waves.

UWA channels have been collected so far [3]. Further, conventional statistical assumptions applied in terrestrial and satellite scenarios, for example, Rayleigh distribution for amplitude and Gaussian distribution for ray arrival time, do not hold true in realistic UWA propagation.

To overcome the aforementioned major challenges, we turn to data-driven machine learning (ML) to empower UAC with intelligence capabilities, so as to enable intelligent system optimization and sustainable performance improvement. ML technology enables machines to make predictions or decisions by learning from data observations, without following strictly static programs.

Recently, ML has received much attention as a key enabler for the evolution of terrestrial wireless communications. For instance, deep learning (DL) has been advocated for demodulation in OFDM systems [4]. For 5G wireless systems, an efficient online channel state information (CSI) prediction scheme has been designed, which learns from the historical data via deep neural networks (DNN) [5]. These successes illuminate the feasibility and potential benefits of exploring ML for wireless communication systems.

Different from existing works, this article focuses on UAC systems and networks, which feature in unique characteristics and give rise to new challenges and opportunities for ML. On this topic, there have been some preliminary explorations and results. For example, NATO has developed a decision tree-based approach that chooses the fastest modulation scheme among several predefined single-carrier signals based on CSI [6]. In [7], adaptive transmission based on reinforcement learning (RL) is presented for time-varying UWA channels, which formulates the adaptive problem as a partially observable Markov decision process. Yet, the evolution towards ML-based UACs is still at its infancy, lagging far behind that for the terrestrial counterpart in terms of both breadth and depth. To fill this gap, this article contributes to illuminating a pathway for ML research to embrace the unique challenges and opportunities in UACs, with focus on some advances that ML has shown promise for UACs.

The ensuing article is organized as follows. The next section reviews several categories of ML algorithms, emphasizing on those that we will suggest for UAC applications. We then delve into our proposed application of ML for the physical layer (PHY), with focus on adaptive modulation and coding (AMC). Following that we expand the discussion to multiple layers of the UAC networks (UWANs) and highlights several major open issues and future directions in ML-based UAC systems, followed by concluding remarks in the final section.

Overview of ML Techniques

Typical ML algorithms can be generally classified into four categories depending on the nature of the dataset for learning as well as the feedback mechanism available to the learning system. They are *supervised* learning (SL), *unsupervised* learning (UL), *semi-supervised* learning (SSL), and RL, where supervised, unsupervised or semi-supervised learning indicates whether the available data samples are labeled, unlabeled or a mix of both, and a reinforcement scheme provides feedback in terms of rewards or regret to navigate the learning process.

SL: It refers to the ML task of inferring an input-output mapping function from labeled training data, where the dataset contains observations of both the input objects and the resulting output values.

UL: It seeks to infer a function that describes the inherent structure or underlying distribution from unlabeled data, that is, the observations do not include the output values such as regression or categorization outcomes.

SSL: It involves both labeled and unlabeled data for training. Leveraging a blend of both the SL and UL techniques, it typically starts with inferring a rough model for the input-output mapping function from labeled data, and then makes use of the unlabeled data to improve the modeling accuracy.

RL: Inspired by behavioral psychology, RL deals with learning tasks when feedback of the instanta-

Algorithm	Category	Accuracy	Training speed	Functionality
Decision tree	SL	Medium	Fast	Classification, regression
Random forests	SL	High	Slow	Classification, regression
Support vector machine	SL	Medium	Fast	Classification, regression
k-nearest neighbors (k-NN)	SL	Medium	Fast	Classification
K-means	UL	Medium	Fast	Clustering
Naive Bayes	SL	Low	Fast	Classification
(Deep) Neural networks	SL, UL	High	Slow	Classification, regression clustering
Q-learning, deep Q Network	RL	Improve continuously	Slow	Behavior optimization
Multi-armed bandit (MAB)	RL	Improve continuously	Slow	Behavior optimization

TABLE 2. Comparison of different ML algorithms.

neous reward is available. It concerns how learning agents ought to take actions in a certain environment based on feedback, in order to maximize the cumulative rewards over time.

Based on the above categorization, Table 2 summarizes and compares several commonly-used ML techniques in the literature. Among them, DNN, which is a typical DL algorithm, has recently stood out as a powerful ML tool that owes its fast development to the increase of both available data volume and hardware computational capability. Mimicking the way that the human brain processes light and sound into vision and hearing, DL tools make use of the representation power provided by multiple hidden layers in an artificial neural network for both supervised and unsupervised learning.

ML for UAC Systems

With the advances in wireless technologies, research interest in UACs has expanded from traditional simple point-to-point transmissions to multi-point communication networks. To facilitate interoperability of diverse UAC nodes, an OSI-based standardized UWAN protocol stack has been built to characterize the communication functions of UAC systems using five abstraction layers, namely, PHY, data link layer, network layer, transport layer and application layer. Noticeably, due to the lack of accurate and usable models for the complex channel characteristics and adverse node features in harsh UWA environments, there are critical issues to be addressed at each of these layers, beyond the capability of existing model-based wireless solutions.

To solve these unique challenges in UACs, ML technology presents a great potential, thanks to its capability to effectively extract the underlying relationship among key parameters of UAC systems from data, even in the absence of any predefined models or prior knowledge. ML is expected to offer major performance enhancement to UAC systems, which will in turn facilitate better exploration and protection of the precious marine resources. For in-depth illustration, next we elaborate on ML techniques at the mission-critical PHY layer.

ML in PHY

At the PHY, UAC seeks to explore the UWA channel characteristics and select suitable communication schemes for effective data transmissions. Extensive efforts have been spent on UWA channel modeling, and various terrestrial wireless PHY solutions have been tailored for UAC based on the assumed UWA models. However, such solutions derived under a simplified channel model or an idealized condition cannot achieve stable performance or even fail to work effectively in practice, due to the high uncertainty and complexity of realistic UWA channels. In contrast, ML as a data-driven solution, is appealing for its capability to implicitly learn the underlying channel and intelligently adapt the communication schemes and parameters at the PHY. As such, ML-aided UAC systems have the potential to track and adapt to dynamic and complex communication scenarios, with inherent immunity to channel modeling uncertainty. Along this line, several channel-dependent tasks can benefit from ML, including AMC and precoding at the transmitter side, as well as channel prediction, demodulation and decoding at the receiver. Among them, AMC critically impacts the bit error rate (BER) and throughput of UAC systems in the presence of highly uncertain and dynamic UWA channels. Next, we delve into the ML-based AMC design.

AMC is appealing to UAC by tracking channel dynamics and adaptively switching among a set of modulation and coding schemes (MCS) for the most efficient transmission. Existing AMC methods follow the extensive literature for terrestrial wireless communications, which can be categorized into two groups: one is based on instantaneous CSI obtained from channel estimation, and the other is based on statistical link information (SLI) inferred through long-term observations or historical knowledge. Unfortunately, the former category often fail to work effectively for UAC due to the lack of a general channel model that accurately represents diverse and complicated UWA propagation. Meanwhile, the SLI-based methods hinge on long-term channel statistics and thus suffer severely from slow response to fast dynamics and sudden changes in UAC links. These drawbacks of conventional methods motivate us to develop an ML-aided AMC approach.

From the perspective of ML, the AMC procedure can be viewed as a classification problem that aims to partition the feature space into non-overlapping feasible regions for each MCS. Along this line, Fig. 1 shows our proposed ML-aided AMC model for UAC systems, which has an added ML-based AMC classifier to optimize the transmission format. After performing model training prior to actual deployment, we treat the AMC classifier as a black box, with the input being the real-time channel state and the output being the corresponding optimal MCS. Further, to continuously update this classifier as new data arrive during operation, an online learning mechanism is incorporated. Such a closed-loop ML-aided AMC solution offers salient capabilities of both sustainable self-enhancement and broad applicability to various operation scenarios. Next, we give a guideline on developing and applying this ML-aided AMC framework.

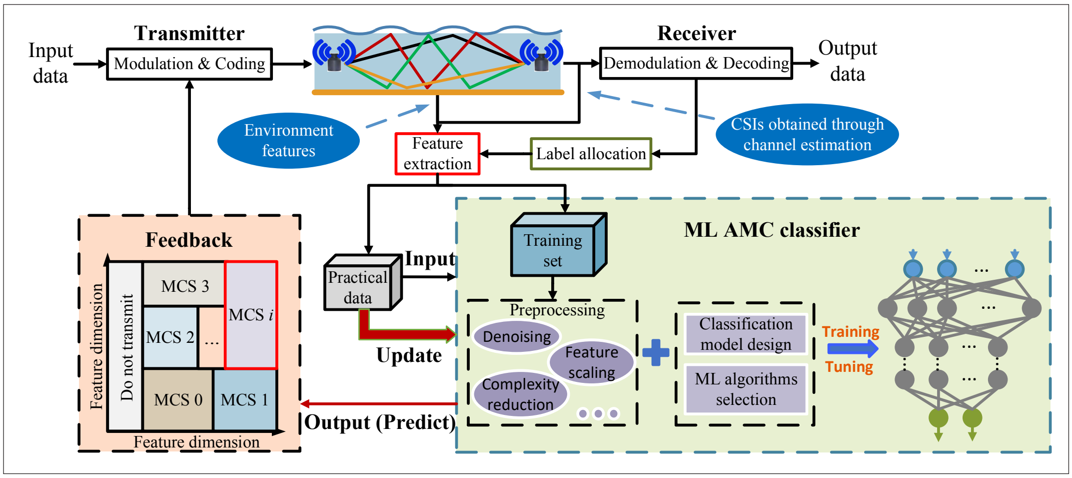

FIGURE 1. ML model for AMC in UACs.

Guideline for Employing ML in UACs

In this subsection, we outline the relevant principles in employing ML techniques for UACs, by offering useful step-by-step guidelines in solution development and practical implementation.

Problem Modeling: First, it is essential to fully understand the target problem before applying ML (i.e., define the input and the corresponding output), and then build a proper ML model for training.

Data Gathering: For ML-based UACs, it is vital to collect a sufficiently large training dataset of good quality. Unfortunately, either real data collection from field experiments or synthetic data generation via simulations is highly challenging in UWA scenarios. First, the high cost of ships and hardware maintenance make marine experiments expensive to conduct; further, usable experimental data is not easy to collect due to the harsh and dynamic aqueous conditions. Second, there are limited simulation tools to generate reliable synthetic data, because of the lack of accurate UAC channel models. Thus, it is of foremost importance to construct a rich training set by gathering and sharing a large volume of data from field experiments and/or even generating realistic data from a generative adversarial network that is informed by both real and synthetic data.

Data Preprocessing: Both the quality and quantity of the initially constructed training set need to be enhanced continuously. This step includes the following critical components:

- Denoising: to remove the data points that contain incorrect information
- Feature scaling: to streamline the dimensions of all feature quantities so as to avoid the learning results being dominated by features with wider ranges
- Complexity reduction: to alleviate the burden on computing resources and training time, by transforming the original data into a new form with little information loss, through dimensionality reduction (e.g., principal component analysis (PCA)) and data condensing (e.g., k-means).

Model Parameter Tuning: The model prediction ability shall be refined through iterative adjustments of model parameters, until reaching desired performance. By now, the trained ML model is ready for deployment in practice.

Learning on the Fly: During the online deployment stage, semi-supervised learning can be used to keep learning from the operating scenarios to update the ML model, so as to continually enhance the performance in terms of model accuracy and scalability.

Training ML models takes practice. For those who are new to ML or want to get results quickly, it is advised to extract some key features based on domain knowledge and experience to represent the original data, and train the model using simple ML algorithms. These two strategies help to obtain usable outcomes while greatly reducing the demand for computing resources and training time. When further improvement of model intelligence is desired, one can turn to a DL-aided AMC framework that utilizes the data itself for intelligent feature extraction and sustainable performance improvement.

Illustrating Examples

To illustrate the potential of ML for AMC, we consider a convolutional coded multicarrier multiple frequency shift keying (CC-MC-MFSK) UAC system and adopt the weighted k-NN (w-kNN) algorithm for its simplicity and robustness. It illustrates a quick solution that yields useful ML outcomes for AMC, and serves as a benchmark for more powerful ML algorithms. Three MSC schemes with various data rates are considered: MCS1) CC-MC-2FSK with code rate 1/2 and data rate 227 bps, MCS2) uncoded-MC-4FSK with data rate 911 bps, and MCS3) uncoded-MC-8FSK with data rate 1,366 bps. For data gathering, we collect a set of real-world channel measurements from three field experiments conducted by our research group (i.e., Ganhe reservoir (October 2011), Fuxian lake (July 2013) and Danjiangkou reservoir (June 2016)). These data are then organized and labeled. Specifically, each input is the measured channel condition represented by a six-dimensional CSI feature set, including the CSI-induced receiver signal-to-noise ratio (SNR), time delay spread, time delay of the strongest path, total power of the first three paths, total power of all paths, and the normalized amplitude of the first path. For each channel input, the corresponding MCS output is labeled by testing the three predefined MCSs and selecting the best one that meets the BER requirement at the highest data rate. Eventually, a dataset of 3,610 observations is made available, with labels covering all three MCS schemes.

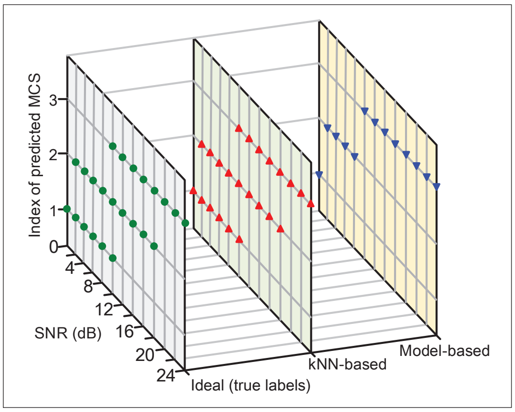

FIGURE 2. MCS prediction outcomes vs SNR.

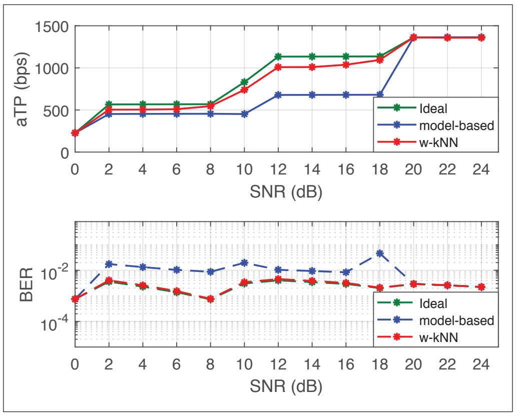

FIGURE 3. Average throughput (aTP) and BER vs SNR.

Given the dataset, we learn the mapping function from the input channel condition to the output MCS by training a w-kNN classification model (a.k.a. classifier). The learned results are evaluated on test data in terms of the optimality of the predicted MCS (Fig. 2) and the achieved performances in terms of average throughput (aTP) and BER (Fig. 3), with comparison to a traditional model-based method that only uses SNR as the MCS switching metric. Noticeably, since the channels are characterized by multi-dimensional features rather than SNR alone, each SNR may correspond to multiple optimal MCS choices with different data rates, and hence aTP and BER do not vary monotonically in SNR. Instead, the BER curves stay rather flat around the required BER threshold, while the aTP improves as SNR increases. As confirmed by Figs. 2 and 3, this simple yet effective ML classifier obtains near-ideal solutions with salient robustness in tracking channel dynamics under different operation scenarios, thanks to its immunity to channel modeling uncertainty.

Open Issues and Opportunities

Having delved into the PHY layer to illustrate the benefits of ML to UACs, we now offer an outlook on ample research opportunities and open issues across multiple layers. For UWANs, their unique node characteristics give rise to adverse impacts on the link quality. *First*, the water current causes unavoidable node mobility, resulting in nontrivial Doppler effects and high dynamics in the topology of UAC systems. *Second*, the noise sources consist of not only the ambient noise but also the echoed self-noise, both of which are quite complex. The ambient noise coming from other sound sources such as breaking waves, raindrops, and nearby ships, is usually enlarged in the water to become much larger than that in the air. Meanwhile, since communication nodes in UWANs are often mounted on mobile platforms, the self-noise generated by mobile carriers cannot be ignored. *Third*, marine nodes are usually powered by batteries that are expensive to recharge or replace in underwater conditions, and hence the network lifetime is a limiting factor in design and implementation. All these adverse node characteristics make well-known designs for terrestrial wireless networks fail to work well underwater, for example, MAC protocol, routing protocol, and so on. In contrast, many terrestrial wireless systems operating in benign environments do not necessarily need to adopt ML, since mature model-based techniques are proven efficient and near-optimal. In Table 3, we summarize major potential applications and functionalities at each layer of UWANs that can benefit from ML, and suggest some use cases where ML should be carefully designed in response to their unique challenges of UWANs.

ML in Data Link Layer: The data link layer provides a node-to-node data transfer link between two directly connected nodes through two main functions: logical link control and medium access control (MAC). By introducing ML and utilizing its capability in learning multi-variable functions and capturing the underlying relationship in dynamic environments, the data link layer can adapt its behavior to link changes. Specifically, ML offers at least three promising opportunities for performance enhancement at this layer: i) link-adaptive selection of the optimal packet size to maximize the efficiency of automatic repeat-request (ARQ) systems, ii) intelligent MAC protocol design to overcome channel uncertainty, and iii) adaptive power control to reduce the energy consumption of data link transmission.

ML in Network Layer: The network layer aims to find the optimal source-to-destination paths for routing and delivering data packets. A feasible approach to alleviating issues of non-uniform channel conditions and adverse node characteristics is to adopt reinforcement learning, which can make globally optimal decisions by progressively learning useful historical information of both the UWA environment and node behavior, such as CSIs, network topology, contact nodes, link performance, energy usage, and so on. In doing so, the routing overhead is reduced, leading to a sustainable network with extended lifetime. Along this line, reinforcement learning can be adopted in topology control, path routing and relay node selection to build intelligent routing protocols. It is also promising to address the unique challenges caused by the sparse deployment of underwater nodes and highly mobile marine platforms in modern UWANs, such as node localization, optimal node deployment and location selection, and so on.

Smarter UACs: Inspired by the concept of smart cities, there is increasing interest in building smarter UAC platforms through the integration of ML with the Internet of Underwater Things (IoUT). As a worldwide network of smart interconnected underwater objects with a digital entity, the IoUT is capable of acquiring all sorts of useful information and exchanging data among connected nodes. Hence, future UWANs may

Application	Layer	Advantages	Suitable ML class
Channel prediction and estimation [8]	PHY	1) Improve efficiency by eliminating large-scale matrix operations in traditional methods; 2) Improve prediction ability through learning from historical information.	SL
Demodulation and Decoding [9]	PHY	1) Improve robustness by addressing model deficiency, i.e., no well-established UWA channel model; 2) Improve efficiency by tackling algorithm deficiencies, e.g., high complexity of optimal receivers.	SL
AMC [10]	PHY	1) Offer immunity to channel modeling uncertainty; 2) Improve the ability of dynamic channel tracking by managing all relevant PHY parameters.	SL, RL
MAC design [11]	Data link	1) Improve efficiency by learning from the traffic load to reduce idle listening and overhearing; 2) Reduce latency by analyzing channel behavior and switching transmission strategy accordingly.	SL, RL
Power control [12]	Data link	1) Intelligently update the power control decisions in lieu of the traditional static control strategy; 2) Improve the trade-off between energy consumption and data transmission.	SL, RL
Routing protocol [13]	Network	Learn from both environmental data and node contact history to: 1) reduce packet delay via adapting to the variable topology; 2) improve energy efficiency via making optimal routing decisions.	RL
Relay node selection [14]	Network	1) Improve robustness by removing the impact of imperfect CSI estimation; 2) simplify the process of relay selection; 3) improve the efficiency of residual energy allocation.	RL
Resource management [15]	Cross multiple	Make optimal global resource management actions through: 1) enhancing communication-related protocols intelligently; 2) eliminating nonfunctional and energy-wasteful activities.	RL

TABLE 3. Opportunities of ML in UWANs.

embrace unprecedented capability in environmental sensing and data collection, and thus can detect and acquire much enriched data sources, including not only various types of marine communication information, but also useful environmental messages such as ships, routes, locations, and so on. Such enriched data sources and volumes offer tremendous opportunities to benefit the design of ML-aided smarter UAC systems, through high-quality feature extraction, learning from historical observations, and making intelligent decisions over a joint space of all relevant system parameters. Such a shared platform for smarter UACs is critical for UWANs in particular.

Conclusion

The increasing demand for exploring and managing the vast marine resources has underscored the importance of UAC research. This article contributes to analyzing major challenges in UAC and laying out potential solutions from an ML perspective. Relevant ML techniques are categorized, and promising applications of ML in UWANs are outlined and discussed in a layer-by-layer manner. In particular, ML solutions to the performance-critical functional block of adaptive modulation and coding for UAC systems are delineated, including ML model considerations, design guidelines and preliminary results. By highlighting open issues and opportunities, this article seeks to attract researchers to engage in this research and collaboratively build intelligent UAC systems with superior performance.

Acknowledgments

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