ML-based Joint Doppler Estimation and Compensation in Underwater Acoustic Communications

Yung-Ting Hsieh, Zhuoran Qi, and Dario Pompili
Department of Electrical and Computer Engineering
Rutgers University–New Brunswick, NJ, USA
{yungting.hsieh,zhuoran.qi,pompili}@rutgers.edu

ABSTRACT

With the rapid growth of Machine Learning (ML) in recent years, more and more technical issues, which were usually solved by model-based solutions, have an opportunity to be solved with data driven solutions. Underwater Doppler effect was tackled with model-based solutions in tracking the motion and compensating the interference caused by multipath Doppler effect in communications. However, a too complex model for the harsh underwater conditions leads to massive computation and becomes an obstacle for the real-time Doppler compensation. In this research, we adopt ML techniques to solve underwater Doppler issues. We propose ML-based tracking and a tracking-aid ML-based compensation. The results show that joint tracking and compensation method have tap choosing accuracy 96.7%, 86.7%, 100% and 93.3% in different power ratios of the two-dominant path condition with fine tree, linear Support Vector Machine (SVM), quadratic SVM and cubic SVM.

KEYWORDS

Doppler effect, Doppler tracking, Doppler compensation, Decision feedback equalizer, Machine learning, Data driven solution

ACM Reference Format:
Yung-Ting Hsieh, Zhuoran Qi, and Dario Pompili. 2022. ML-based Joint Doppler Estimation and Compensation in Underwater Acoustic Communications. In *The 16th International Conference on Underwater Networks & Systems (WUWNet'22), November 14–16, 2022, Boston, MA, USA.* ACM, New York, NY, USA, 8 pages. https://doi.org/10.1145/3567600.3568139

WUWNet'22, November 14–16, 2022, Boston, MA, USA

ACM ISBN 978-1-4503-9952-4/22/11…$15.00
https://doi.org/10.1145/3567600.3568139

1 INTRODUCTION

Overview: Nowadays, underwater wireless communications have played an important role in the military, commercial, and scientific fields [1]. The applications include natural resource exploration, scientific ocean exploration, oceanic environment monitoring, and communications between submarines [2]. For many of these applications, a reliable underwater wireless communication system over long-range distances is in urgent demand. Given the harshness of the environment, improvements at the physical layer are very important for underwater wireless communications and networks–including static sensing nodes are beneficial to the applications in communication between Autonomous Underwater Vehicles (AUVs), Bouys and water floor base stations. One of the main-stream underwater wireless communications is UnderWater Acoustic (UWA) communication, which suffers low attenuation and covers a communication range of up to kilometers [19]. However, the underwater acoustic wave has a speed of as slow as 1500 m/s, leading to high multipath delay. Moreover, the Doppler effects caused by the dynamic water wave and moving AUVs make the UWA communications even more challenging [14].

Motivation: In UWA communications, the Doppler effect results from the motion of the transmitter, the motion of the receiver, and the motion of the water wave [12, 23], leading to the frequency shift in the received signals and making the demodulation difficult at the receiver. In previous works on tackling with the Doppler estimation, the assumed conditions are usually simple. The simplest condition is: one object is moving and the other is fixed, when only considering one path of the transmission without any multipath, for example, reflections from the sea surface or the seafloor. The Doppler effect can be effectively solved with the conventional methods like Digital Phase-Locked Loop (DPLL) combined with Decision Feedback Equalizer (DFE) or autocorrelation combined with compensation algorithms [21, 22]. Recently, more works are dedicated in the multipath Doppler effect situations, where the multipath signals from different angles of arrivals cause the issue of demodulation to be more sticky. In the model-based solutions for the multipath Doppler effect scenario, the most common way is to enlarge the number of taps in the feedback compensation loop. For each multipath, one more tap is needed for doing the Doppler compensation, and one additional tap in the feedback loop of the time synchronization is required. Although the model-based methods have been proved to compensate the multipath Doppler effects effectively, there are challenges still unsolved: (i) If the number of the strong reflections is unknown at the receiver, the number of taps for the compensation becomes hard to be designed and decided, which leads to compromised performance of the Doppler compensation. (ii) The multipath effect caused by the strong reflection is more difficult to be compensated since the number of the paths is hard to get and the ratio between the direct path and other paths is also hard to acquire in the model-based solution. (iii) When using a large number of taps in the feedback loop of the Doppler compensation, the high computation cost becomes an obstacle if we want to do the real-time Doppler compensation further.

Proposed Solution: In this paper, we propose a joint ML-based method to do tracking and compensation for the severely influenced signal by the Doppler effect in different settings of the environment. An ML-based tracker is trained with Phase Shift Keying (PSK) signals corresponding to different relative speeds of the Transmitter (Tx) and Receiver (Rx). When the Rx receives signals, the received signals will first be classified by the ML-based tracker. After tracker is an ML-based digital compensator. The compensator is designed based on the previous methods of combining the DPLLs and the DFE, where the DPLL loops in the feedback filter are transferred to taps for training the compensator. Each tap has been designed to solve a Line of Sight (LOS) received signal plus a strong path reflection which we call the Second Dominant Path (SDP) condition as shown in Figure 1(a). It can be tuned with different K, which is defined by the power ratio of the LOS and other paths in the Rician channel and Doppler shifted frequency ratio D, which is the frequency ratio Doppler shifted frequency f_s over the central carrier frequency f_c. After training with the data set and added features from ML-based Doppler tracking output, the compensator can choose the most appropriate tap for the DFE to deal with the severe Doppler influenced signals with the aid of the output of the ML tracker.

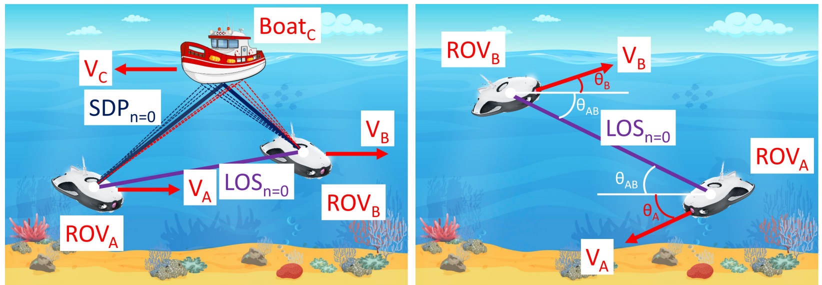
Contributions: In this research, we demonstrate the feasibility of taking machine learning into a field, which model-based solution is taking the vast majority. Although the data-driven-only method might perform just passable, we design a new architecture to let data driven method stand upon the shoulders of model-based methods such as Doppler compensation. The ML-based joint Doppler tracking and compensation method is proposed. We present the ML-based compensation with validation in the same underwater channel environment. The contributions are as follows:

- Multipath feedback tap loops for compensating multipath Dopper interference have become popular recently. We adopt data driven methods to simplify the feedback loop without scarifying compensation performance.
- In the Binary phase-shift keying (BPSK) Rician channel simulation, we confirm the relationship between the power ratio K, and acquired Bit Error Rate (BER).
- The simulation results show that the joint tracking and compensating can improve the accuracy from the worst case solely with ML 26.7% to up to 100% jointly with sacrificing a little in prediction speed and it has BER improvement over ten times when choosing the proper DFE tap.

Article Organization: Section 2 presents the relevant publications and the background. Section 3 describes our proposed solution, including the model-based solution and the data driven solution. Section 4 shows the performance of our proposed solution. And in Section 5, we draw the conclusion.

2 RELATED WORKS AND BACKGROUND

In [17], we propose a modulation method, namely Orthogonal Frequency Division Multiplexing (OFDM)-based Pulse Position Modulation (PPM), which shows high robustness in underwater wireless optical communications, but does not suit the UWA communications due to the high multipath delay. In [18], we study the video transmissions in UWA channels by conducting experiments in a swimming pool. A full-duplex underwater communication self-interference cancellation is investigated in [10]. We simulate and emulate the underwater communication in Binary Phase-Shift Keying (BPSK) modulation to demonstrate how we solve multipath interference via beamforming techniques. In [16], we derive a novel modulation scheme named Circular Time Shift Modulation (CTSM) for UWA. However, the Doppler effect isn't discussed in our previous works. In [15], we propose the Spatial Modulation-based Orthogonal Signal-Division Multiplexing (SM-OSDM), which defends against the Doppler effects by spatial diversity. Authors in [6] discuss the channel model of multipath, but the Doppler effect is not considered. There have been massive model-based methods for solving the Doppler effect in underwater communications, including DFE, PLL etc. These methods require massive computation when the model becomes more complex to tackle the harsh underwater environment. In the previous study, the underwater environment is simply assumed to be the direct path, sea surface reflection and seafloor reflection. In [3] the multipath Doppler tracking is improved by a dynamic programming-inspired method, called Online Segmented Recursive Least-Squares (OSRLS) to sequentially



(a) (b)

Figure 1: (a) An illustrative example of a Line of Sight (LOS) with a Second Dominant Path (SDP) Doppler scenario. Where two components dominate, the behavior is best modeled with the Rayleigh and Rician fading channel; (b) Example where the Doppler frequency shift impacts the $LOS_{n=0}$ channel component. Additionally, the process of the relative speed $\hat{v_{AB}}$ estimation with the corresponding angles between ROV "A" and "B" are presented.

estimate the time-varying non-uniform Doppler across different multipath arrivals. The piece-wise-linear Markov model is used to approximate the nonlinear time distortion further simplify the procedure. In [13], an optimization framework for tracking Doppler shifts in acoustic motion is proposed by combining the Frequency Modulated Continuous Waveform (FMCW) to enhance the accuracy. Authors in [5] propose a DFE with multiple DPLLs to compensate the phase shift caused by Doppler effects in multipath delay in UWA communications, which enhances the system robustness effectively compared with traditional DFE with only one DPLL. Authors in [11] propose a joint Doppler scale estimation and timing synchronization method in UWA channels, where the Superimposed Hyperbolic Frequency Modulation (HFM) is applied as the preamble. The simulation results show that the Doppler factor can be estimated correctly, and the deviation of timing synchronization can be corrected effectively. In [8], a new architecture of ML circuit is presented. The voltage based Resistive Processing Unit (VRPU) design combined with the diode based activation function circuit expands the feasibility for adopting analog Neural Network into more cases. Based on the concept of VRPU, more analog machine learning circuits are presented in [7]. SVM with kernels including linear, polynomial and Gaussian kernels have been proposed to work on the top of VRPUs. These circuits can serve as a pre-stage of the hybrid system, which only triggers the powerful digital ML circuit to achieve a power-saving anomaly detection. Recently we proposed a ultra-low power analog recurrent neural network design [9]. By reusing the hardware resources in the circuit, it explored the possibility to apply smart system into micro-Watts level. Above ML designs are prospective to execute the DFE smart chooser proposed in this research in multipath Doppler effected channels.

3 PROPOSED SOLUTION

In this section, we demonstrate the model-based solution, which is the fundamental theory of the Doppler compensation. To realize effective Doppler compensation as well as reducing the computation cost, we propose our data driven solution, which is composed of ML-based Doppler tracking and ML-based Doppler compensation. We propose the joint Doppler tracking and compensation to effectively address the issue of Doppler frequency shifts in UWA communications.

Model-Based Solution: As for the Doppler tracking, we start from the simplest set of available sensors and only consider information about ROVs' absolute velocity and their planned trajectories shown in Figure 1(b). These parameters allow communicating partners, denoted as ROV$_A$ and ROV$_B$ to estimate the potential Doppler shift of the direct path LOS$_{n=0}$ with the projected velocities $\hat{v_A}$ and $\hat{v_B}$ onto the common LOS direction θ_{AB}, the Doppler shifted frequency f_s is expressed as,

$$f_s = f_c \frac{(\hat{v_A} + \hat{v_B}) \cos \theta_{AB}}{c}. \tag{1}$$

The term c is the velocity of the sound wave in the water and f_c is the frequency of the carrier wave. $\hat{v_A}$ is the horizontal component of the speed V_A can be acquired as $\hat{v_A} = V_A \cos \theta_A$, same as $\hat{v_B}$ in the Figure 1(b). If we consider another strong reflection, which is a signal reflected by a boat as we label "C", the Doppler effected frequency between A, B and C can be presented as,

$$f_s = f_c \frac{[(\hat{v_A} + \hat{v_C}) \cos \theta_{AC} + (\hat{v_C} + \hat{v_B}) \cos \theta_{CB}]}{c}. \tag{2}$$

where θ_{AC} and θ_{CB} are common LOS directions between "AC" and "CB", correspondingly.

Assume $x(t)$ is the transmitted signal at the baseband. With a carry frequency of f_c, the transmitted signal at the passband $s(t)$ can be expressed by,

$$s(t) = \text{Re}\left\{x(t) \exp[i2\pi f_c (t - t_0^{Tx})]\right\}, \tag{3}$$

where Re$\{\cdot\}$ means the real part; t_0^{Tx} is the starting time point of the transmission.

On the Doppler compensation side. During the conventional demodulation based on combining the DFE with a DPLL (as shown in Figure 2(a)), the feedforward filter compensates the channel response of the direct signal, the DPLL compensates the nonlinear component of the phase shifts $\phi_0^{NL}(t)$, and the feedback filter compensates the channel responses of the multipath signals. In the upgrade demodulation shown in Figure 2(b), DFE with additional DPLLs, more DPLLs are added to the feedback filter to suppress the phase shifts of the multipath signals. Among the feedback loops, the term b_{fb}^H combined with summation $\phi_1 ... \phi_k$. The performance is improved, but the computation cost is increased. Moreover, in real-time communications, the process of DFE with additional DPLLs cost more time and result in a higher delay in transmissions. In our work, we propose an ML tap chooser in the feedback loop 2(c). Each tap in the ML-based solution b_{fb}^H combined with summation $\phi_1 ... \phi_k$ we define as a unique setting T_p, and two neighbor taps are labeled as T_{p-1} and T_{p+1}. For solving one direct path $LOS_{n=0}$ plus SDP condition setting, we must consider the combination in power ratio of the $LOS_{n=0}$ and other paths K and Doppler shift frequency ratio D, to reduce the complexity and save time.

Data Driven Solution: In the data driven solution, the first target is Doppler tracking with supervised machine learning. The existing Doppler tracking methods are almost model-based and the model-based techniques are mature. However, for a heavy multipath effect influenced environment, the accurate estimation requires a high complexity model with the Cross-Ambiguity Function (CAF) or the Single-Branch Autocorrelation (SBA) [20]. Data driven gives an opportunity to avoid the complex model. In the data driven method, we shrink the conditions to most likely appear Doppler shift as labels. For example, in underwater communication, neither Tx or Rx can have a velocity the same as a jet. We train the machine learning model with reasonable velocity induced phase shift of the received signals.

Linear Discriminant Analysis (LDA) can be used to perform supervised dimensionality reduction by projecting the input data to a linear subspace consisting of the directions which maximize the separation between classes. The dimension of the output is necessarily less than the number of classes, so this is, in general, a rather strong dimensionality reduction and only makes sense in a multiclass setting, i.e., Doppler shifted phases from different parameters. LDA can be derived from simple probabilistic models, which model the class conditional distribution of the data $P(\angle r(t)|\phi(t) = \phi_k)$ for each class ϕ_k, a situation of the multipath Doppler scenario. Predictions can then be obtained by using Bayes' rule, for each training sample $r(t) \in R^d$,

$$\begin{aligned} P(\phi(t) = \phi_k|\angle r(t)) &= \frac{P(\angle r(t)|\phi(t) = \phi_k)P(\phi(t) = \phi_k)}{P(\angle r(t))} \\ &= \frac{P(\angle r(t)|\phi(t) = \phi_k)P(\phi(t) = \phi_k)}{\sum P(\angle r(t)|\phi(t) = \phi_l)P(\phi(t) = \phi_l)}, \end{aligned} \tag{4}$$

and we select the class ϕ_k that maximizes this posterior probability.

Naive Bayes methods are a set of supervised learning algorithms based on applying Bayes' theorem with the "naive" assumption of conditional independence between every pair of features given the value of the class variable. In the Normal, as known as Gaussian distribution. In the Kernel Distribution, the "kernel" distribution is appropriate for predictors that have a continuous distribution. By default, the kernel is the normal kernel, and the classifier selects a width automatically for each class and predictor. Given class variable $\angle r(t)$ and dependent feature vector ϕ_1 through ϕ_k, we have the following classification rule,

$$\begin{aligned} P(\angle r(t)|\phi_1, ..., \phi_k) &\propto P(\angle r(t)) \prod_{i=1}^{K} P(\phi_i|r(t)), \\ \hat{r} &= \arg\max_r P(\angle r(t)) \prod_{i=1}^{K} P(\phi_i|r(t)). \end{aligned} \tag{5}$$

The SVM function stated as follows: Maximize the geometrical margin subject to all the training data with a functional margin greater than a constant. The functional margin is equal to $W^T X + b$, which is the equation of the hyper-plane used for linear separation. As we deal with non-linearly separable conditions, we use different kernel functions to project data onto high dimension space to solve the problem, which can not be tackled in the initial space. A quadratic decision function capable of separating non-linear data is used [4]. The geometrical margin is proved to be equal to the inverse of the norm of the gradient of the decision function. The functional margin is the equation of the quadratic function. W is called the Objective function satisfying,

$$W(\Lambda) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) \tag{6}$$

Here, x, y and α are the parameters on the hyper-plane. W is called the Objective function, which is a quadratic equation and has to be maximized; it is a function of all $\alpha_1 ... \alpha_n$ represented as Λ corresponding to our Doppler features $\phi_1 ... \phi_k$. Cubic SVM type classifier is employed where the kernel function of the classifier is cubic given as $K(x_i, x_j) = (x_i^T, x_j)^3$. Subsequently, we introduce the joint Doppler tracking and compensation solution. The Doppler effect allows the measurement of the distance, velocity and acceleration between a transmitter from water and a receiver on the seafloor by

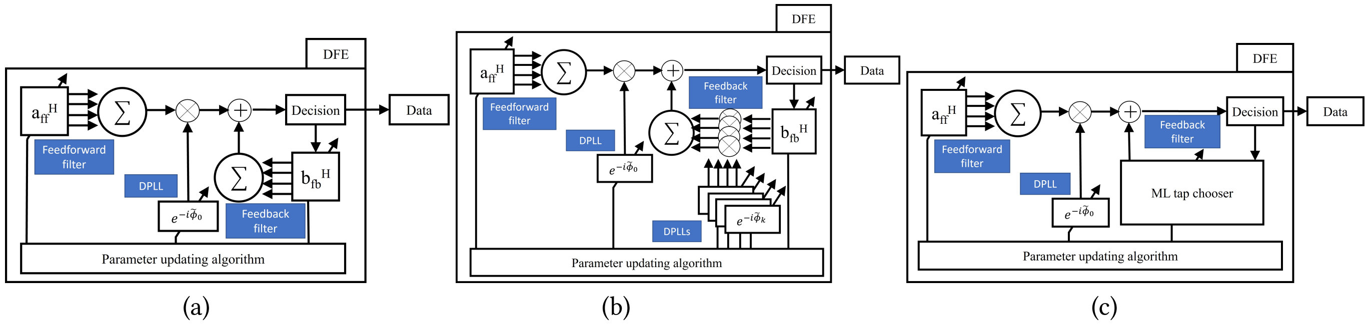


Figure 2: (a) Conventional Decision Feedback Equalizer (DFE) with only one Digital Phase-Locked Loop (DPPL) for solving simple Doppler effect; (b) Additional DPLLs modified DFE for solving multipath Doppler effect; and (c) ML-based DFE for more complex Doppler effect scenario. a_{ff}^H is the tap of the feedforward filter. b_{fb}^H is the tap of the feedback filter.

Table 1: Doppler tracking with different ML methods under different Doppler shift in LOS.

	Fine Tree	Linear Discriminant	Gaussian Naive Bayes	Kernel Naive Bayes	Linear SVM	Quadratic SVM	Cubic SVM
Accuracy	73.3%	100%	56.7%	63.3%	100%	100%	100%
Total cost	8	0	13	11	0	0	0
Prediction speed (obs/sec)	160	160	140	13	160	150	160
Training time (sec)	2.19	1.57	3.41	32.45	1.8	1.95	1.71

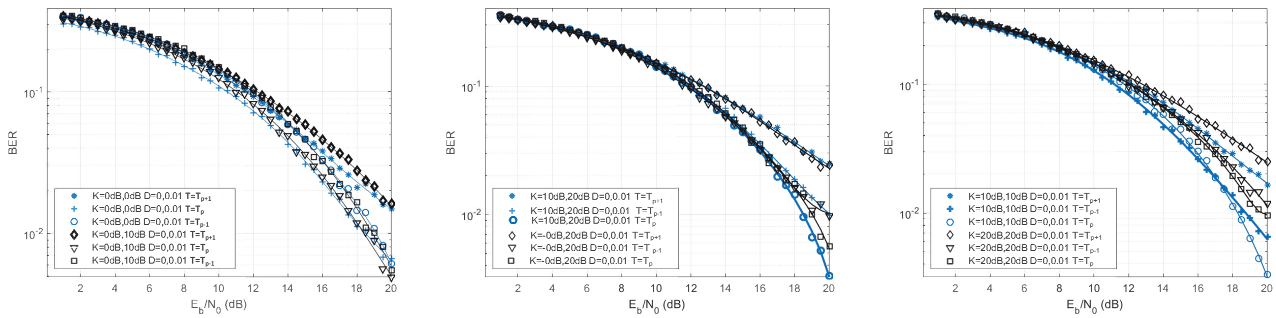
observing how the frequency received from the transmitter changes as it approaches the transmitter, is overhead and moves away. We present an ML-based Doppler tracking by training with time domain Rician channel frequency shifted signals. For example, we can shift signals by 100 Hz, 300 Hz or 500 Hz in a carrier wave that has a central frequency 10 kHz to train the classification learner for $D = 0.01, 0.03, 0.05$. Each Doppler shift represents one relative velocity condition of the $LOS_{n=0}$ and the multipath influences caused by the channel. The time signal is sampled with 1000 points as the source of the training data, which means 1000 features for training the ML model. The data driven method simplifies the potential Doppler frequency shift compensation correspond to the difficult Doppler effects introduced by the real situation. Unlike the model-based method, the data driven can (i) avoid unnecessary frequency shift band thus reducing the complexity of the model, and (ii) decrease the number of self correlation or DPPLs and thereby save the computation time.

In order to valid the proposed ML-based DFE, a more complex Doppler scenario is considered. Compared with previous works, which consider moving objects and their direct path and multipath on the main path, we simulate the Doppler effected signals with Rician channel, the K-factor in the channel help to generate more complex condition, which means not only the main path of the direct and reflected paths are considered, other dominant paths can be considered with their separate parameters as we put them together.

In the LOS plus SDP scenario, as the object A is moving toward x direction at velocity v_{Ax}, object B is moving toward x direction at velocity v_{Bx} and object C is moving toward x direction at velocity v_{Cx}. When the object A is transmitting signals to the object B, the object B receive the LOS signal from A affected by the relative velocity between A and B. Besides, another strong reflection path from object C is considered and analyzed as another dominant path in the Rician channel, i.e., SDP. The SDP signal is affected by the relative speed between A and C. Under this condition, the Rician channel provides these two dominant multipath influences by different K factors and different Doppler phase shifts.

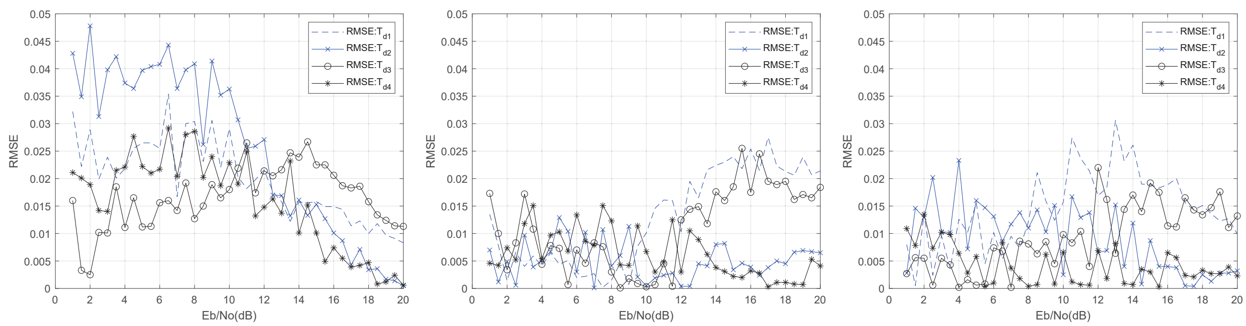
4 PERFORMANCE EVALUATION

In this section, massive simulations in underwater channels are deployed. The ML-based Doppler tracker is trained to directly classify the shifted frequency. Secondly, we design an ML-based tap chooser in the feedback loop for the Doppler compensation. The tap chooser is trained with different combinations of the more complex underwater Doppler environment, i.e., a major LOS plus an SDP. We train the tap chooser with different K and D combinations in these two signal paths. Afterward, we jointly do the Doppler compensation with the tracking result and the tap chooser to achieve a fast and power saving Doppler compensation compared with the existing model-based methods.



(a) (b) (c)

Figure 3: BER of joint ML Doppler compensation with the BPSK in a LOS plus SDP in Rician fading channel with the following parameter setting: (a) $K = 0$ **dB**, 0 **dB and** $K = 0$ **dB**, 10 **dB; (b)** $K = 10$ **dB**, 20 **dB and** $K = 0$ **dB**, 20 **dB; and (c)** $K = 10$ **dB**, 10 **dB and** $K = 20$ **dB**, 20 **dB; as** $D = 0.01$ **comparing the performance of the intended tap** T_p **and neighbor taps** T_{p-1} **and** T_{p+1}**.**



(a) (b) (c)

Figure 4: Root-Mean-Square Error (RMSE) of joint ML Doppler compensation in a LOS plus SDP in Rician fading channel comparing with the conventional DFE with the following parameter setting: (a) T_{d1}**; (b)** T_{d2}**;(c)** T_{d3}**;(d)** T_{d4}**. RMSE:** T_{d1} **means the root-mean-square error between** T_p **and neighbor taps** T_{p+1} **in Figure 3 and so on, i.e., the cost for ML to choose the neighbor tap in the feedback loop.**

ML-based Doppler Tracking In the underwater communication simulation, the software we use are Matlab and Simulink on a desktop equipped with AMD Ryzen 9 5950X 16-core CPU (overclocked to 4.0 GHz), Patriot DDR4 128 GB RAM (overclocked to 3333 MHz), Samsung 970 EVO Plus 2 TB SSD (read speed up to 3500 mb/s) and Nvidia Quadro RTX 8000 GPU. The simulated signals are modulated and demodulated with BPSK. The channel we use are the Rayleigh channel, which is Rice with shape parameter $K = 0$, i.e., heavy multipath/saturation conditions and Rician with low, medium, and high K, i.e., different energy fractions on the LOS. We first confirm that the result of using the Rayleigh channel is dovetailed nicely to the Rician $K = 0$ setting. Rician fading is a stochastic model for signal propagation anomaly caused by partial interference of a radio signal by itself - the signal arrives at the receiver by several different paths, which is called the multipath effect, and at least one of the paths is changing, including getting longer or shorter in length. Rician fading channel is the channel that considers when one of the paths, typically a LOS signal or some strong reflection signals, is much stronger than the others. In Rician fading, the amplitude gain is characterized by a Rician distribution. Rayleigh fading is considered a special case of Rician fading for when there is no LOS. In such a case, the Rician distribution, which describes the amplitude gain distribution in Rician fading, reduces to a Rayleigh distribution mathematically as $K = 0$. It is notable that Rician fading itself is a special case of Two-Wave with Diffuse Power (TWDP) fading, the characteristic can be described by two main parameters. The first one, K, is the ratio between the power in the direct path and the power in the other scattered paths. The second one, Ω, is the total power from both paths and acts as a scaling factor to the distribution, $K = \frac{v^2}{2\sigma^2}$, $\Omega = v^2 + 2\sigma^2$. By tuning K, we can evaluate our proposed solution under different multipath conditions of the LOS. As the Signal-to-Noise Ratio (SNR) increases, the performance of the higher K signal in the Rician channel can be very good.

Table 2: Performance of ML-based joint Doppler tracking and compensation under different K in Rician channel in LOS+SDP.

	Fine tree	Linear SVM	Quadratic SVM	Cubic SVM
Accuracy	96.7%	86.7%	100%	93.3%
Total cost	1	4	0	2
Predict speed (obs/sec)	150	140	140	140
Training time (sec)	1.79	1.64	1.68	1.67

It is notable that the Doppler effect has a certain level influence among low SNR to high SNR. In the low SNR condition, parameter D has a greater influence on the performance of the communication. On the other hand, in the high SNR condition, the power ratio K affects the performance more. The ML-based Doppler tracker is trained and validated with cross-validation in 5 folds (k=5). Different models, including fine tree, linear discriminant, Gaussian naive Bayes, kernel naive Bayes, linear SVM, quadratic SVM and cubic SVM are trained with a number of 30 data having Doppler shift D=0.01, 0.05, 0.1 separately applying random SNR (E_b/N_0) between 10 dB to 19 dB. To do the supervised machine learning training and validation, 1000 samples in the time domain serve as 1000 features and are labeled with corresponding configurations, which means a 30×1000 dataset. The result shows linear discriminant, linear SVM, quadratic SVM and cubic SVM have better performance. Naive Bayes methods have compromised performance since in the assumption the features are independent to each other. However, the features in the Doppler shifted signal is not totally independent. With the platform spec shown previously, the prediction speed can achieve 140 to 160 obs per second except for the inefficient kernel naive Bayes.

Joint ML-based Doppler Compensation In the Doppler compensation, we compare two configurations in machine learning. One is the DFE tap chooser without aid from the ML-based Doppler tracking output, and the other one is with the aid of the tracking output. Before the Doppler compensation, we firstly investigate the influence on the Bit Error Rate (BER) on different K and D. The increase of K reduces the non-LOS paths interference to result in a better performance on BER. The more serious Doppler shift, which means higher D, is leading to a compromised performance on BER. The compensation is designed to solve the one LOS plus one strong reflection problem. The ML-based Doppler compensator is shown in Figure 2(c). It is modified from Figure 2(b), which is the higher level design for solving the harsh multipath Doppler interference based on Figure 2(a). By making taps in the feedback loop in some fixed parameters, then we design a machine learning tap chooser to decide which tap to be used in the Doppler compensation feedback loop. In order to demonstrate our proposed solution, we generate the number of 30 data that having Doppler shift $D = 0.01, 0.05; 0.05, 0.05; 0.01, 0.1$ when $K = 0$ dB and $K = 0$ dB, 10 dB; 10 dB, 10 dB; 0 dB, 20 dB when $D = 0.01$ separately applying random SNR E_b/N_0 between 10 dB to 19 dB. The complexity of the interference from two major paths is higher than only one path, making the dataset more difficult to be classified through machine learning methods. The highest accuracy is still less than 85%, which indicates using the sampled data solely as the dataset for the machine learning is not enough. To overcome the issue, we create a joint method, in which we do tracking first to get the information of the Doppler shift. Next, we feed the tracking result as new features into the tracking-aid tap chooser, i.e., joint Doppler tracking and compensation tap chooser. The new dataset is 30 data samples with the increment of 10 features sweep. With 1050 features the performance of the joint tap chooser is shown in Table 2. We choose the top four classification methods including fine tree, linear SVM, quadratic SVM and cubic SVM, which to be considered in the joint Doppler compensation. The joint Doppler tracking and compensation tap chooser sacrifice about 10 obs/sec in the prediction speed but get better accuracy in the validation. Other methods in LOS+SDP with different K can achieve accuracy above 85%. Figure 3 shows the performance of the Doppler compensation after adopting the chosen tap in the DFE in different combinations of K. Beside the chosen tap, we also show the performance of two neighbor taps which indicate the performance when the tap is not chosen to the best one, compromised performance of the second or third tap in the sequence and the root-mean-square errors is shown in Figure 4. This shows the difference between the conventional DFE and our proposed ML-based method. In the conventional method, massive computation guarantees the most suitable tap is generated. However, the ML-based method is choosing the tap in the feedback loop instead of generating. It leads to the possibility to choose the neighbor tap, getting compromised Doppler compensation, which is the cost for the simpler data driven method compared with the conventional DFE. Moreover, it is notable that Figure 3 showing the performance of the two main paths are not entirely following the trend we acquire previously, which lower K is getting fair performance because of the influence of the DFE and the interference caused by two strong paths.

5 CONCLUSION

In this research, we propose a machine learning Doppler compensation method with the joint of smart tracking and tap choosing. The proposed solution adopt the concept of the DFE model as well as join the machine learning to accelerate computation and to save power without sacrificing much performance. We demonstrate the feasibility of the ML-based Doppler tracking. As encountering the harsh Doppler multipath influenced environment, although the ML-based DFE tap chooser has compromised performance, the tracking-aid joint solution help to increase the accuracy by sacrificing only 10 obs/sec out of 150 obs/sec to 170 obs/sec. In the one direct path plus a strong reflection condition. The joint solution has been validated with different power ratios of the LOS and other paths, the ratio of the Doppler frequency shift and the carrier wave frequency. The result shows the great potential that the machine learning aided model is an ideal candidate for the next generation in real-time Doppler compensation. Other new types of classification methods with even neuron networks will be discovered and applied to the underwater Doppler tracking and compensation. In the near future, similar concepts can be applied to any other field, which has similar background conditions. The data driven methods can be investigated and become a good catalyst to the model-based solution.

ACKNOWLEDGMENTS

This work was supported by the NSF NeTS Award No. CNS-1763964.

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