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Machine learning based underwater optical-acoustic communications channel switching for throughput improvement.

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Machine Learning based Underwater Optical-Acoustic Communications Channel Switching for Throughput Improvement

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Abstract – Underwater Wireless Optical Communication (UWOC) is at the cutting edge of subsea networking, offering high capacity, low-latency, energy-efficient connectivity that offers many advantages over the acoustic standard which has been embedded in submersible systems for a century. One aspect in which it fails currently, however, is transmission range and reliability, only achieving 10s of metres in range and requiring Line of Sight (LOS) to operate, meaning that changes of turbidity and ambient noise originating from the Sun or ROV light sources can actively interfere with transmission success. An investigation into machine learning algorithms has been carried out that aimed to enable a modem to utilise environmental sensors to interpret the UWOC channel and make accurate predictions on whether it should transmit, potentially store in memory for later transmission, at the cost of latency, when the channel is clearer, or use another mechanism such as acoustics or radio frequency to transmit promptly, with minimal latency. It was found using a synthesized dataset compiled using simulation and a regarded photon-counting model, that common ML algorithms such as Support Vector Machines (SVM), Random Forest (RF) and Narrow-Neural Networks (N-NN) can successfully use parameters such as distance, transmission power and extinction coefficient to determine the nature of the channel, thus, whether to transmit or not, with classification accuracies greater than 98.5% providing a reliable method to switch between acoustic and optical signalling in response to channel conditions in the latter, maximising data throughput, reliability whilst managing energy consumption and latency.

I. Introduction

There are many key issues with simply mass implementing UWOC technologies, the key among them is probably the "link frailty," LOS and low propagation range. What link frailty refers to in this instance, is that light as it propagates from point-to-point interacts with whatever particles and molecules that is in its path in a complex manner, seawater is specifically a challenge for light to propagate through as the ray of light interacts with the salts and organic chemicals that are suspended within causing scattering and absorption. What compounds this complexity is that the potential bodies of water a UWOC system could be implemented in are diverse in their propagation properties [7], thus, a rigid approach to developing modems is assured to enable only rigid approaches to networking in an environment that can be dynamic and inherently treacherous to communication in general, but specifically UWOC. Thus, to address this, developments in resource constrained Machine Learning (ML) [8] and Edge Computing (EC) [9] are a compelling vector from which to embed this flexibility in Underwater Wireless Communication Networks (UWCN) of the near future. This investigation builds on prior works in the field and aims to propose a smart mode switching technique for hybrid UWOC/UWAC networks that utilises an array of sensing mechanisms and ML to diagnose local channel conditions, judging whether to commit to utilising the frail UWOC channel according to those conditions or use UWAC (or some alternative mechanism, the key technology is UWOC centred) to transmit. In the underwater network, architectures that can use different modes of communication have the potential to enable superior performance that those enabled by only one mechanism as the physical layer constraints achieve different performances and fail in different scenarios, however, to facilitate this functionality to its potential methods of judging when to use acoustics and when to use visible light is required. The proposed mechanism is explored and implemented in MATLAB and is validated as being possible through robust analysis.

II. Background

The multi-physical layer wireless network has emerged both as a proposed mechanism to implement improved networking mechanisms for the networks of the near future. Typically, the proposition is to utilise a robust technology then combine it with a less-robust but high-capacity wireless optical link to offer a channel that is far superior for carrying the dense data required for cutting edge applications. As such, the UWOC/UWAC network has been proposed as a potential mechanism in the Underwater Wireless Communication Network (UWCN) to facilitate robust data transmission yet open the potential for higher capacity transmission. Previous works have investigated this potential across a variety of network topologies and applications [10-11]. The initial work that was relevant to this investigation was [12] which was a field data acquisition mission which enabled aggregation of much needed data regarding water columns and their optical properties at various points in the day, locations etc. This investigation, and a follow up [11], showed how the various parameters at play in the water column contributed to successful propagation of a packet from point-to-point in a vertical link for a specific water column off the coast of Western Sahara. Demonstrating that combinations of solar, downwelling-irradiance noise and a changing extinction coefficient contributed to a change in success rate versus distance from the source. This investigation inspired the research of a specific mode switching mechanism for a given scenario, initially, a fuzzy logic (FL) method was investigated that aimed to consider these parameters and the presence of an interfering object to actively monitor the local channel and judge whether to transmit via UWOC or defer through an optic fibre link to another node but it could be expanded to UWAC similarly as the mechanism was developed merely under the principle of adapting from UWOC to another, more robust mechanism. The problem with this fuzzy logic, however, was that the simple Mamdani ruleset [11,13] low-computation and simple to implement and is not generalisable to different columns of water or different depth points within that column of water. Thus, to develop a more generalisable mechanism that can adapt to different columns of water intuitively without having to fine tune a fuzzy logic controller, an investigation in to developing a machine learning mechanism was carried out. The field of underwater hybrid communication is emerging progressively with publications dedicated to exploring different methods of robustly communicating the data in the required manner from source to sink. One area that has not seen work specifically is how to drive this switching between modes on a technical basis, this work aims to build on the work we have carried out previously which used fuzzy logic as a mechanism for mode switching using ML algorithms towards more advanced mechanisms autonomous in the near future.

III. SIMULATION APPROACH

This work was implemented in MATLAB using the toolboxes and libraries available, potentially gains will vary according to language. The first problem was the sourcing of a dataset to train the ML algorithm on, as this is a concept that is challenging and expensive to implement in a practical situation to produce data, it was decided that a dataset would be synthetically produced in a Monte Carlo manner [14]. This involved defining upper and lower boundaries on the data based on what is found naturally and in the anthropomorphic systems themselves. Table I shows the values utilised for the Monte Carlo dataset generation process. With these boundaries defined, the dataset was randomly generated using MATLAB's uniform random number generator, within the specified minimum and maximum values. This dataset was then input into the underwater photon-counting model developed in [15], which incorporates factors such as emitted power, directionality, and extinction coefficient to output a Successful Delivery Ratio (SDR) based on the Bit Error Ratio (BER).

TABLE I, THE RANGE OF VALUES AND DISTRIBUTIONS USED TO CREATE THE SYNTHETIC DATASET

	Range of Values	Discrete/Continuous (Res)
Distance (m)	1-100	Continuous
Extinction coefficient (m^{-1})	0.01-3	Continuous
Bitrate (Mb/sec)	0.5-20	Discrete (0.5)
Transmission Power (W)	5-50	Discrete (5)
Packet size (kb)	0.5-5	Discrete (0.5)
Background Counting Rate	1×10^{-9} - 1×10^{15}	Continuous Logarithmic

The model utilised is found in [10,11] and was als

o investigated prior. This distribution was selected to cover for a diverse range of possibilities at all points in the network as the initial distribution is unknown, thus, it gives the network a diverse dataset from which to work with, future works in the field and data aggregation will refine the distribution with new knowledge. Regarding potential realism in the simulated data, it was developed with prior awareness of the ranges of values typically found with each variable for the UWOC channel as seen in water column explorations, so they are all within the range of what is expected. To simulate the wireless VLC channel, the BER is calculated for a clear water optical channel assuming LOS links. The power level of the signal reaching the receiver, denoted as P_R Los, is determined using formula 1 [15].

$$P_{R\,LOS}= P_T\eta_T\eta_R L_{pr}\left(\lambda, \frac{d}{\cos\theta}\right)\frac{A_{Rec}\cos\theta}{2\pi d^2(1-\cos\theta_0)} \qquad (1)$$

Where P_T is the transmission power, η_T and η_R are optical efficiencies of the transceiver and receiver respectively, $L_{pr,}$ the propagation loss factor as a function of wavelength, λ, and distance z is given by formula 2.

$$L_{pr}\,(\lambda, z) = \exp(-c(\lambda))z \qquad (2)$$

Perpendicular distance, d, between the transmitter and re-ceiver plane, θ is the angle between the perpendicular to re-ceiver plane and the transmitter receiver trajectory. A_{Rec} is the receiver aperture area and θ_0 is the laser beam diver-gence angle. The accepted stochastic model for coherent photon arrival in photon counters is the Poisson distribu-tion, where this rate, during the gated receiver slot, T, is given by formula 3 [1]. The photon is the fundamental par-ticle of light and therefore, probability of arrival at the trans-mitter is inherently tied to the BER.

$$r_S=\frac{1}{T}\left(\frac{P_R}{R_D}\right)\frac{\eta_D}{h_v} \qquad (3)$$

Where R_D is the data rate, η_D is the detector counting effi-ciency, P_R is the output from formula 7, h is Planck's con-stant and v is the frequency of the photon. Formula 4 shows the method utilised to determine the bit error ratio of the

VLC channel, BER_O, where $r_1 = r_d + r_{bg} + r_s$, $r_2 = r_d + r_{bg}$, r_d is the dark counting rate and r_{bg} is the background counting rate and the complementary error function "erfc" is given by formula 5.

$$BER_O = \frac{1}{2}\ \mathrm{erfc}\{\frac{r_1T\text{-}r_0T}{\sqrt{2}(\sqrt{r_1T}+\sqrt{r_0T})}\} \quad (4)$$

$$\mathrm{erfc}(\psi)=\frac{2}{\sqrt{\pi}}\int_{\psi}^{\infty}\exp(\text{-}\gamma)\ d\gamma \quad (5)$$

Once the BER has been obtained for both communication methods, the SDR of a given packet size in bytes can be given by formula 6 where m is the size of the packet in bits.

$$p^m_{successful}(\gamma)=[1\text{-}BER(\gamma)]^m \quad (6)$$

Clearly, this is not ideal as it is going to produce combinations and observations that are not going to be found, however, if enough observations are produced in this manner, tending towards infinity, then the ML algorithm will have been trained on all possible observations including all that will be found, encapsulating the model that formulae 1-6 describes pragmatically. The dataset was designed to be balanced with a 50/50 split. The output SDR is given as a ratio value between 0 and 1 where 0 means there is no chance of successful transmission and 1 means assured delivery. It was decided to implement this scenario as a classification problem where the aim was to process the input data and deliver a judgement in the form of, 0 for "Do not send using UWOC" and 1 "Send packet using UWOC". The decision where to set the threshold for transitioning between classes 0 and 1 was decided upon the principle "that anything less than absolute certainty for UWOC is unacceptable due to the link frailty" thus, 100% success would be qualified as a 1 and anything lower would be 0. Having developed this pipeline so that it would successfully and readily produce the observations and judgements based upon the reputable model, the process was looped until it would provide a dataset of 10,000 observations where there was a 50/50 split between classes 0 and 1, thus, it was entirely balanced. Generally, classification datasets on repositories like UCI differ significantly in observation count from hundreds to millions. 10,000 was selected as a starting point based on prior works in the field using the UCI epilepsy [16] dataset which had initially has 11,501 observations and enabled relatively robust classification. Based on this prior success, this number of observations was chosen. At this juncture, having produced the dataset, it was exported in a .csv as a standard to be utilised for future experiments then implemented in MATLAB's Classification Learner Toolbox. This stage was implemented using K-fold validation with 5 folds and a 10% holdout of the data for testing after the training and validation process. From this point, the ML algorithms were selected for testing, these were a Quadratic-Support Vector Machine (Q-SVM) [17], the Bagged Trees Ensemble (BTE) [17] learner which is functionally like Random Forest (RF) and finally, a Narrow Neural Network (N-NN) [17]. These algorithms were picked as they are some of the best performing classification learners available to engineers, but they all fall under different strategies, a statistical method, a rule-based method, and an Artificial Neural Network (ANN) method [18,19]. Each model was running three times through the process, this was done to eliminate any outliers that could appear due to the fundamental probabilistic nature of ML and create a more balanced view and analysis of the proceedings. In addition to the varying parameters that were input into the dataset generation process, it is key to discuss that there were constant variables that were intrinsic to the LOS photon-counting simulation model covered in [15], these are given in table II.

TABLE II , CONSTANT VALUES USED IN THE SIMULATION

Parameter	Value
WVLC Efficiencies of Transmitter and Receiver	0.9
Pulse Duration	1ns
Transmitter Inclination Angle	0 °
Beam Divergence	68°
Detector Counting Efficiency	16%
Dark Counting Rate	1MHz
Receiver Aperture Area	$0.01m^2$
WVLC Data rate	10Mb/sec
Acoustic Transmission Power	8W
Acoustic Data Rate	62.5kb/sec
Sleep Mode	0.025W
Transmissions per Day	48
Packet Size	4000 bits
Battery Size	216000

In addition, some communications-based analysis was carried out into the results to interrogate how this mechanism could save energy and otherwise improve performance on the physical layer. This was carried out similarly using a simulation strategy where the proposed mechanism performance was compared to continuing to utilisation of single acoustic mode. This ties the proposed mechanism back for comparison to the current standard technology and to observe how it improves upon it. This simulation was carried out under the principle of a single link connecting a source to a sink transmitting a constant packet size with a constant transmission power, this was then used to interrogate how it effects the link latency and power consumption at the transmitting node to show how such a mechanism could improve performance. To further evaluate the complexities, it was prudent to investigate how the changing channel conditions faced by the network would affect performance on the physical level, we defined circumstances for 5 fuzzy concepts as an abstract chance over a period of time with a finite number of transmissions driven by the algorithm's sensing of the channel and corresponding decisions made as to which mechanism should be utilised for packet transmission. These condition definitions are as seen in table III. It is assumed that generally that this situation will always be good for acoustic, however, clearly this is not going to be the case, a future study will observe this same problem potentially as a multi-class to add another layer that will enable a "store option" when both channels fail.

TABLE III, CONDITION VALUES USED IN THE SIMULATION

Channel Conditions	WVLC Transmission Chance	Acoustic Transmission Chance
Great	100	0
Good	75	25
Middling	50	50
Bad	25	75
Dismal	0	100

It is assumed that the ML algorithm energy consumption and latency will be negligible compared to the high values for the acoustic communications parameters, this simulation additionally considers sleep time to understand and compare how long the two networks could last. The ML hyperparameters applied to train and test the models on the synthetic data are seen below in table IV.

TABLE IV, ML HYPERPARAMETERS USED IN THE SIMULATION

Parameter	Value
Random Forest Learners	30
Learner Type	Decision Tree
Ensemble Method	Bag
N-NN Number of Fully Connected Layers	1
N-NN First Layer Size	10
Activation Layer	ReLU
Iteration Limit	1000

From this juncture, the corresponding simulation was carried out.

IV. Results And Discussion

The results of the initial phase of the research are as follows, they were evaluated across several key parameters that enable investigation into the appropriateness of them algorithms regarding the resource constrained nature of the network in terms of computational complexity, energy efficiency and accuracy. To select the models and their hyperparameters, a sub-investigation was carried out that involved varying the architecture of the algorithms. It was found that the application favoured a neural network with a single fully connected layer with 10 neurons (the default MATLAB Narrow Neural Network) compared to structures and 30 learners were used for the RF algorithm. Q-SVM was selected as the relationship between the inputs were non-linear and there needed to be an element of nuance to find the most effective hyperplane. A similar process was carried out for the other architectures experimenting with hyperparameters and options such as feature selection, tending towards optimisation of the models in terms of the parameters found in table II. It was found that applying feature selection hampered the model's ability to accurately select the correct mode to transmit the packet. The evaluation process involved a 5 K-fold validation process and 90/10 training and testing holdout ratio. Table V and VI shows the results of the investigation. As can be seen, despite the randomly generated nature of the dataset, the ML algorithms were all relatively successful in associating a given pattern with the corresponding outcome observation, seemingly successfully getting to point where the conclusions are near convergent on what the actual model would conclude, with accuracies ranging between 98.3% and 99.2% which is considered a success when reflected upon in previous ML classifier works [20].

TABLE V, COMPARISON OF THE THREE ALGORITHMS THROUGH ACCURACY AND MODEL SIZE METRICS

Model	Model Size (kb)	Test 1 Accuracy	Test 2 Accuracy	Test 3 Accuracy
N-NN	~6	98.6%	98.6%	99.2%
Q-SVM	~30	98.7%	98.8%	98.7%
BTE	~920	98.3%	98.7%	98.3%

TABLE VI, COMPARISON OF THE THREE ALGORITHMS THROUGH PREDICTION SPEED

Model	Prediction Speed 1 (Obs/sec)	Prediction Speed 2 (Obs/sec)	Prediction Speed 3 (Obs/sec)
N-NN	260,000	240,000	250,000
Q-SVM	230,000	230,000	230,000
BTE	25,000	26,000	25,000

The success, however, came at various costs and some algorithms achieved this at lowest costs than others. It can be seen from the data that the BTE algorithm had the lowest overall accuracy between the three algorithms and additionally, achieved this requiring a significant model size that is almost a MB in size. Furthermore, using prediction speed as a metric for computational complexity, it was the slowest of the three algorithms suggesting that the complexity was highest, this also implies more energy consumption to support this activity, thus, it was determined that this is the least fit for the scenario. Regarding the two other performers, both the N-NN and Q-SVM performed significantly better than the BTE algorithm, both achieving relatively high accuracies with lower prediction times and model sizes. In terms of model size, N-NN performed the best, achieving high accuracies with a model that is only 6kb big. This suggests that it would be potentially easier to integrate into a resource constrained computing systems than the two alternatives. In terms of prediction speed, N-NN and Q-SVM both were quicker at making observations using the high-grade processors utilised for the experiment, achieving 100,000's of observations a second, although not directly comparable to a resource constrained edge processor, it at least inclines towards these two algorithms being compelling to take into a next stage analysis on a small device. Additionally, the performance was further analysed through use of the confusion matrix to interrogate the specific nature of predictions. Fig 1 shows the confusion matrices for each of the algorithms investigated during their transition phase.

As can be seen, a further refinement can take place, the N-NN shows a more even distribution when it fails predictions, corresponding with values in the top right and bottom left of the respective diagrams, the other two algorithms however, show a bias towards falsely predicting to use UWOC when they should be electing to use an alternative mechanism, given the dataset is 10,000 observations in scope, this corresponds with around 1% transmission destined to fail due to the algorithm mispredictions whereas the N-NN is more around 0.45%.Thus. it can be said that refining down is possible as the N-NN is a better performer here than the two alternatives. The proposed method shall allow for the optimal mechanism to be selected for each scenario, maintaining high SDR and data rate as well as low latency a through integrating the UWAC and UWOC technologies so that they operate in the most applicable manner as found in previous paper [10].

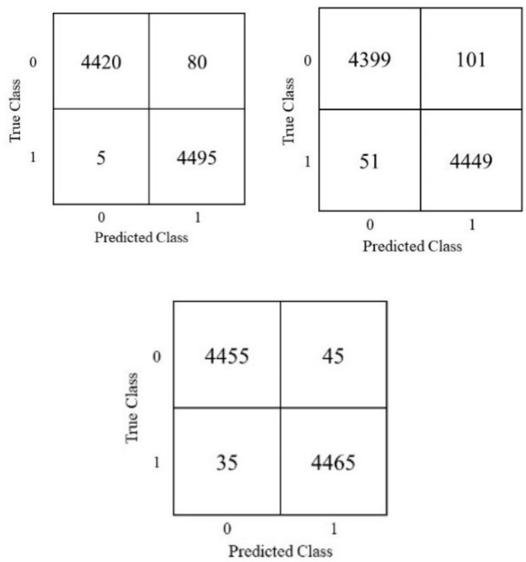

Fig. 1 Confusion Matrices for (top left) Q-SVM, (top right) BTE and (bottom) N-NN.

From the communications perspective, it was found that the mechanism could potentially have a significant effect on the throughput lifespan of a transmitting node from analysis of the physical layer. It was found that from the input data and the mode switching mechanism, WVLC could be effectively managed to allow access to these high bitrate links when applicable allowing for an increase in throughput if necessary. This illustrated in figure 2 which compares bitrate to distance where the dots are successful classification versus the crosses are failed classifications when it came to predicting to transmit the packet.

It can be seen from this figure that essentially bitrate can be as high as 20Mb/sec even at a range of 80m although it is clearly more possible at closer distances and most likely dependent on pristine channel conditions, it also shows that the N-NN is generally effective at classifying whether to do this regardless of distance, however it should be cautioned that this achievement on the smart algorithm being implemented to determine channel conditions as figure 3 shows the scatter plot for the N-NNs predicted UWAC mode switch. It shows that it is effective at preventing when to transmit via UWAC especially where at longer link ranges but also shows how frail these links are generally, as there are times even at close range that it would determine not to transmit.

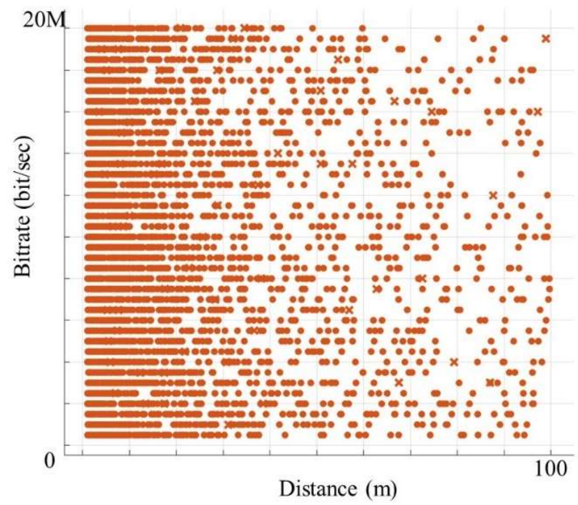

Fig. 2 Scatter plot for the N-NN test 3 transmit via WVLC decision comparing bitrate to distance

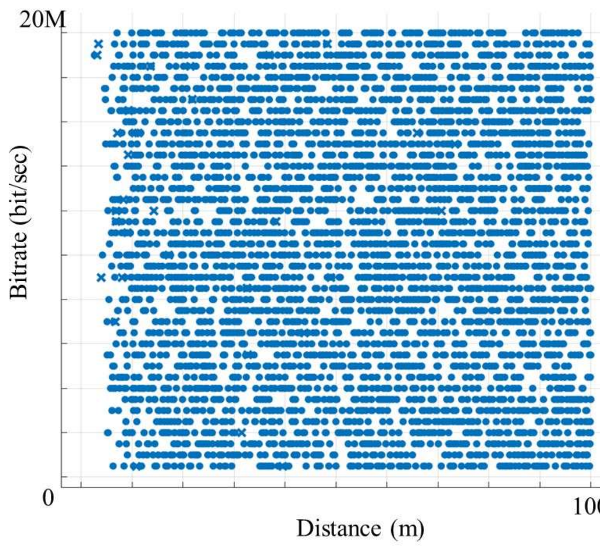

Fig. 3 Scatter plot for the N-NN test 3 transmit via UWAC decision comparing bitrate to distance

TABLE VII, COMPARISON OF PERFORMANCE ACROSS CHANNEL CONDITIONS

Channel Condition	Daily Total Power Consumption (W)	Daily Total Transmission Delay (Secs)	Total Transmitter Lifetime (Days)
Great	216.19	0.0192	969
Good	222.67	0.7824	970
Middling	229.15	1.5456	942
Bad	235.62	2.3088	916
Dismal	242.10	3.072	892

Once again, this shows the importance of having an autonomous manager for this links to sustain UWOC based networks over time in an independent manner. Furthermore, table VII shows how the network performs according to the other relevant parameters in latency, daily total power consumption and thus lifespan. As can be seen, the algorithm controlling the mechanism will lead to reduced transmission delay through access of the higher bitrates and energy consumption reductions will result in a longer life of over 100 days which shall safe recovery costs in to enable recharge. To gain further improvements, studies into reducing the energy demand of sleep mode is necessary as it becomes the dominating factor. This also reveals the prominence of severe delay jitter that will need to be followed up in future works.

V. CONCLUSION AND FUTURE WORKS

In conclusion, a mechanism was proposed that enables a network to switch between UWOC and UWAC according to environmental conditions such as extinction coefficient as well as background noise and various communications parameters such as bitrate etc. This resulted in a proposed N-NN framework that can accurately predict whether to use WVLC or UWAC according to the channel conditions of the more vulnerable underwater optical channel. Furthermore, it was found that this method could enable effectively raise bitrate whilst maintaining robustness as the accuracy of classification with the NN-N was around 99%, this could be increased by generating and adding more observations to the synthetic dataset. In addition, it was found that latencies and energy consumption would reduce, increasing the lifetime of the system for a given battery, however, there will be significant delay jitter that requires resolution. This could be seen as future work. Other future works would be to see how we can apply this multimodal technology to localisation [21] and exploration [22] in the underwater domain.

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