Automatic Shark Detection via Underwater Acoustic Sensing

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***Abstract*—Shark attacks are a rare but ever-present danger for swimmers and surfers in some regions of the world, and the threat of sharks is embedded in popular culture. Traditionally, shark attack mitigation involved the culling of massive numbers of sharks, which has significant environmental and ethical downsides. More recent systems for mitigating the risk of shark attacks involve the manual or automated detection of sharks close to the shore, alerting water users to the potential danger when it occurs and evacuating the water if the shark gets too close. In this work, we present the design of a Shark Warning Acoustic Network (SWAN) that exploits underwater acoustic sensing and communication to automate the spotting, providing a highly accurate and relatively low-cost alternative to visual spotting. We analyze the performance of the SWAN in terms of communication performance and accuracy in alerting water users to dangerous situations, and compare different medium access schemes to identify the most effective network design.**

***Index Terms*—Value of Information, Underwater Acoustic Networks, Shark Warning Systems.**

I. Introduction

While shark attacks are still a rare occurrence, the recorded instances in a series of worldwide hotspots, which include the Caribbean, Australian and South African coasts, have been increasing due to a variety of factors [1]. The habitats of shark populations might be shifting towards more populated areas, due to the changes in prey abundance and warm currents caused by climate change. In addition, the continued development of seaside tourist and residential settings, along with the growth of aquatic sports and tourism, is boosting the number of recreational swimmers, further increasing the likelihood of an encounter with a shark.

Traditional mitigation strategies, which involved the culling of massive numbers of sharks, are no longer acceptable due to their ecological and ethical toll. In this context, early detection of sharks as they approach the shore can be critical: the success of the *Shark Spotters* program in South Africa [2], which used visual and auditory alarms to warn swimmers of shark sightings by observers placed on vantage points next to the beach, shows that coexistence is possible even in dangerous areas, with the proper precautions.

Over the past few years, the research on shark detection has mostly focused on expensive aerial observations, either manned or through the use of drones [3]. These systems are expensive and require significant human effort, and suffer from limited effectiveness in poorer visibility conditions, e.g., due to insufficient lighting or to wave activity. On the other hand, the detection and location of sharks through active or passive sonar is a common practice in ethological research, and has proven to be effective in determining the presence, location, and species of sharks [4]. The deployment of an Underwater Acoustic Sensor Network (UASN) [5] dedicated to this task would mitigate the issues of aerial surveillance, reducing operational costs and providing a reliable, automated platform for shark detection.

However, one of the main challenges in UASN deployment is communication, as the underwater propagation environment is uniquely harsh. Radio frequency communications are possible only over very short distances, so that acoustic communications have to be used in most practical scenarios, as the UASN acronym suggests. The low propagation speed of sound yields much longer signal propagation times than in common radio systems, and complicates the design of underwater communication protocols, which often need to be customized for the targeted application scenario. In particular, to the best of our knowledge, there are no designs for a precise and low-cost shark warning UASN.

This work addresses this gap by proposing an analysis of the trade-offs and the possible ways of measuring the accuracy of a Shark Warning Acoustic Network (SWAN). We define a Value of Information (VoI) function to assess the performance of the system in terms of reducing the danger to water users by giving them timely warnings of sharks, as well as avoiding false alarms. We will hence consider different Medium Access Control (MAC) schemes to tailor the network design to the application, measuring both traditional communication Key Performance Indices (KPIs) and VoI measurements. Capital Expenses (CAPEX) and Operational Expenses (OPEX) are two other important parameters in designing such a network: underwater sonar models can be extremely expensive, and the goal of this work is to design a practical, low-cost SWAN.

The rest of this paper is structured as follows: Sec. II presents the various aspects of the SWAN design, including the sonar detection system, the metrics used to determine the accuracy of the warnings, and the basic communication setup. It also presents a deeper analysis of the communication system, including a discussion of possible MAC configurations. Sec. III describes the evaluation scenario and the performance of these configurations, and finally, Sec. IV concludes the paper and presents some avenues of potential future work.

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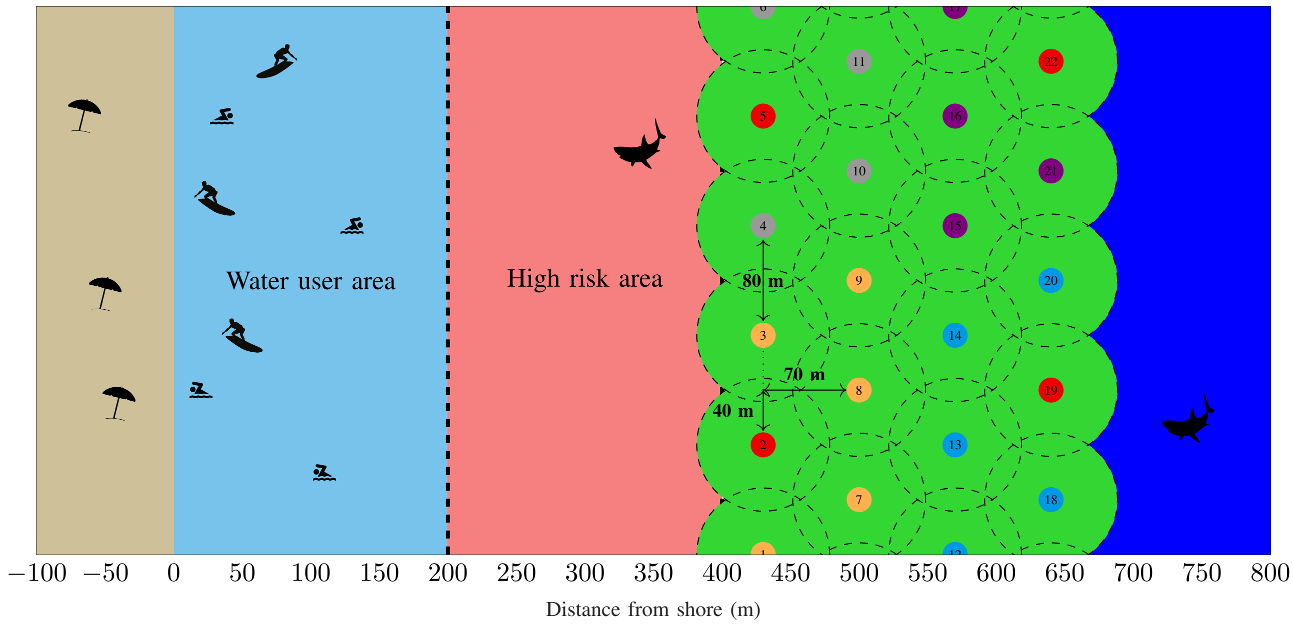


Fig. 1: Shark warning system.

II. Mitigation System Design

Following the approach from the *Shark Spotters* program [2], we design a shark spotting system with different warning levels based on the proximity of the shark. As the shark alarm levels increase, water users are alerted with visual and auditory signals, i.e., flags showing the levels of danger and amplified announcements. They are then encouraged to move closer to the shore as the shark approaches, so as to maintain a safe distance and ensure that evacuation can be conducted quickly. As the highest warning level is reached, a siren sounds repeatedly, encouraging all users to leave the water as quickly as possible.

The final goal of our system is to leave enough time for the users to evacuate the water and, therefore, its design strongly depends on shark mobility. The average speed of white sharks in coastal areas is relatively low, below 2 m/s [6]. However, shark movements are affected by multiple factors, e.g., the presence of schools of fish, and the top reported speed of a white shark in pursuit of a prey is about 12 m/s [7]. If we consider a speed of 3 m/s, a shark would be able to swim about 360 m in 2 minutes: this is a reasonable time for evacuation if all water users have already been gathered less than 50 m from the shore after previous alarms. According to these assumptions, we make the highest alert area start 400 m from the shore.

A. *Shark Attack Mitigation Systems*

Existing shark attack mitigation systems can be divided in two main categories, i.e., deterrence and spotting systems. The first family of systems includes traps and nets, which are used to catch the sharks at a safe distance from the shore (usually 500 m or more) and release them in open water. The most recent development is the use of smart drumlines [8], which can proactively alert coast guard boats if a shark has been caught, limiting the animal's time in the trap. However, deterrence methods have a significant impact on the shark population, in terms of stress and risk of injury, and are regarded as invasive methods [3].

On the other hand, spotting systems are not invasive, as they attempt to identify the presence of sharks and evacuate water users until the danger has passed, without directly affecting sharks or other marine animals. Spotting systems using humans with binoculars [2] or remotely guided drones [3] have been tested over the past few years with relatively good success. However, there are two significant issues with current spotting systems: the first is that they are entirely visual, and depend on the water being relatively calm to successfully see the sharks swimming underwater, and the second is that they are work-intensive. Human spotters or drone operators need to be available at all times, increasing the OPEX significantly with respect to an automated system. We can then consider a system that can spot sharks automatically and under any weather and sea conditions: in order to do so, we need to place imaging sonars underwater, where the effect of waves is limited, and set up a communication system that can relay the position of detected sharks to the shore.

B. *Sonar Sensing*

Multibeam imaging sonar devices [9] can provide several frames per second, but their cost is at least 10 times the price of simpler mechanical imaging sonars. A low power 120° Tritech Gemini multibeam imaging sonar [9] has been used in [10] to successfully detect sharks at least 1.4 m long up to a range of 50 m, but using these devices in a dense network such as the one presented in Fig. 1 will require a very high deployment price.

While mechanical imaging sonar can be acquired at a relatively low price (e.g., the Ping360 [11] costs less than 2000 $ and has a power consumption of 5 W), their main disadvantage is the low scan speed, that depends on the resolution and the range. For instance, in order to provide a range resolution of 4 cm at 50 m, the Ping360 takes 35 s to perform a complete 360° scan. While the company declares that a new software update will lower the scanning time, they need to transmit 400 beams and wait at least 0.067 s for each beam to be reflected back to keep the same resolution and range, given that they have a scanning step of 0.9° and considering a speed of sound of 1500 m/s. Consequently, even with the most efficient implementation, the physical lower bound to the scanning time will be 26.8 s. In order to lower the scanning time of a mechanical imaging sonar, we can use a lower scanning resolution. For instance, the Tritech Micron mechanical scanning sonar [9] has a "very fast" configuration, used for quick object search, which reduces the scanning time by a factor of 4, but degrades the angular resolution from less than 1° to 3.6°. In this case, a circular area with radius 50 m can be scanned in 6.7 s. This would result in the detection of approximately 3 m long sharks at 50 m.

If we consider a maximum scanning range of 50 m, we can then deploy the devices in front of the beach. Fig. 1 shows a map of the deployment: the first 200 m from the shore can be used by swimmers and surfers, but the maximum allowed distance from the shore is progressively decreased to 50 m as a shark gets closer, and a siren sounds immediately if it enters the high risk area, i.e., gets closer than 400 m from the beach. This gives water users at least 2 minutes to reach the shore, assuming that the speed of the shark is lower than 3 m/s [6] and that its presence is immediately detected as it enters the high risk area. The sonar nodes are placed so as to cover a monitoring area that goes from 400 m to about 650 m from the beach: this should give ample time to the system for detecting the shark before it approaches the high risk area, allowing beach guards to gradually raise the warning level as sharks get closer.

The sonar nodes are placed in 4 rows, at a distance of 70 m. The closest row is placed at 430 m from the shore, so as to cover the area up to 400 m. Nodes in a row are placed at a distance of 80 m from each other, and rows are staggered by 40 m, so that the three closest nodes can form an equilateral triangle with an 80 m side, covering the whole space with their sonars. The distances between nodes are included in Fig. 1. In order to avoid acoustic interference between neighbor nodes, we assume the nearby sonar to use a different central frequency, either using a tuneable sonar [9], that can select a central frequency between 500 kHz and 900 kHz, or different sonar models from different vendors [9], [11]. In any case, the acoustic signal generated by the sonar does not interfere with the communication system, as all imaging sonars described in this section use frequencies above 500 kHz.

C. Effectiveness Metrics

The first and foremost effectiveness metric for our warning system is the accuracy of the positioning of the shark: if the control station on shore makes a large error in identifying the shark's distance from the shore, it might cause a significant

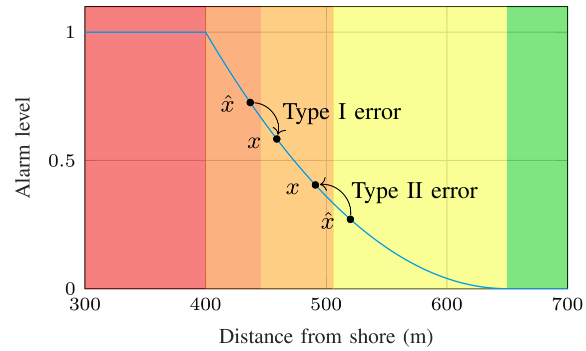


Fig. 2: Alarm level as a function of the distance of the shark from the shore.

danger for water users. The estimated distance $\hat{x}$ should be as close to the real position x as possible. However, not all errors are the same: underestimating the distance of the shark from the shore, i.e., thinking that the shark is closer than it really is, may cause annoyance and worry among swimmers, but will not result in any significant danger. On the other hand, overestimating that distance, i.e., thinking that the shark is farther away than it really is, might cause delays in clearing the water and an increased risk of shark attacks.

Accordingly, we define an alarm function and distinguish between two types of errors, as Fig. 2 shows:

- *Type I errors*, or false positives, happen when the estimated position of the shark is closer to the shore than the real one;
- *Type II errors*, or false negatives, instead occur if the shark is closer to the shore than its estimated position, generating a potential risk for water users.

We use the parameters α and β to control the weight of Type I and Type II errors in the final performance figures, respectively. We define a quadratic alarm function, which gives a larger weight to movements closer to the high risk area: errors in this situation, particularly if Type II, present a much higher risk for water users, and should be weighted accordingly. As Fig. 2 shows, the overall risk factor can go from 0 (corresponding to no sharks within the 650 m line) to 1 (corresponding to the presence of one or more sharks in the high risk area). We can also consider a quantized version of the risk factor, represented by the colored areas in the figures, which can be used to give visual and auditory warnings to water users: following the model in [2], we can use different flag colors and auditory signals to indicate the risk, allowing water users to select the level of risk they are comfortable with and attracting their attention if they need to clear the water quickly. Accordingly, the effect of any error (including both Type I and Type II) on the actual performance of the system will be limited, as long as the real and estimated positions are both in the same colored area. For this work, we chose a quantization step of 1/3, resulting in 5 different flag colors, including the red flag, which represents a risk factor of 1, and the green flag, which represents a risk factor of 0.

TABLE I: List of components and cost of the network deployment for 1 km of coastline.

Component	Cost/unit (€)	n°unit	Total cost (€)
Imaging Sonar [11]	2 000	48	96 000
Ahoi modem	700	48	33 600
Raspberry Pi Zero	10	48	480
Waterproof enclosure [11]	100	40	4 000
Batteries (1 day) [11]	290	40	11 600
Gateway buoy	1 500	8	12 000
Overall cost			**127 440**

D. Communication and tracking system

The nodes also need to be able to communicate with each other, so they are divided into clusters of 6 nodes, which are represented with different colors in Fig. 1. We consider the use of the ahoi [12] low-cost acoustic modem, operating in the bandwidth between 40 and 75 kHz and able to transmit up to 150 m with a datarate of 200 bps. At this range, even the farthest node in a cluster is in range of the cluster head, which is indicated in red in Fig. 1. In order to communicate to the shore, the cluster heads are equipped with Fondriest data buoys, which usually have radio frequency wireless modems with sufficient range and capacity to transmit the data to the shore, batteries, and a small solar panel to recharge them [13]: equipping every node with a buoy would not only be prohibitively expensive (their price starts from 1500 EUR), but also limit the possibility to navigate in that area with ships and vessels, so using clusters of 6 nodes can significantly reduce the cost of the system without negatively affecting the shipping activity in that area.

In addition to imaging sonar and acoustic modem, each submerged node is composed of a low power processing unit, such as a Raspberry Pi Zero, a waterproof enclosure [11] and a lithium battery. Specifically, with a 14.8 V/15.6 Ah battery, we can ensure the operation of the network for several days.

Overall, the system will require 48 nodes per km of coastline, which would correspond to a CAPEX lower than 130 k€ at current prices. However, sensors are long-lived and require limited maintenance, only requiring periodical battery recharges or replacement, and even these can be eliminated with the adoption of soon-to-be-available wave energy harvesting devices [14]. While the initial CAPEX are significant, OPEX are extremely low, particularly when compared to shark-spotting systems that require constant human surveillance or aerial drones (also remotely controlled by human operators).

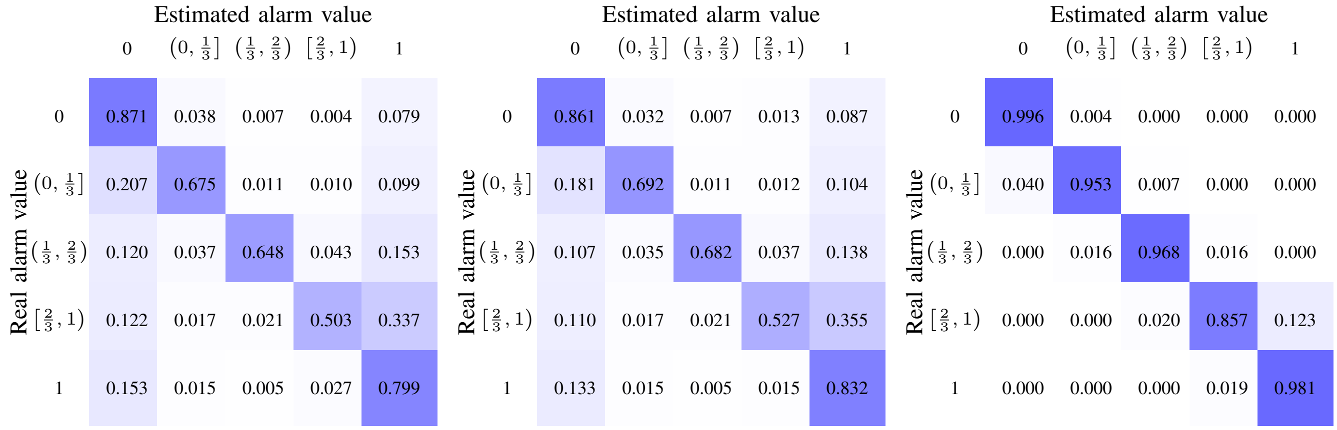
As the sonar requires 6.7 s to perform a full 360° scan, the tracked position can only be updated with that time granularity; additionally, the sonars cannot detect sharks farther than 50 m. Each packet is generated by the UwTracker application layer and contains the shark's 3D position, its velocity, and the tracking measurement timestamp. The overall packet size is 32 B, including a 2 B header containing the source and destination addresses. At the cluster head nodes, received packets are forwarded through the radio interface to the control station on the shore, which stores the information, along with the corresponding packet reception timestamp, and uses it to track the shark by estimating its most recent position and heading. Sensors that transmit to the same cluster head cannot transmit simultaneously, as the interference would prevent either packet from being received correctly. UwTracker generates packets only when the shark is detected, and the MAC configuration impacts the frequency and delay of packet transmission. We consider two different MAC schemes, which have different benefits and drawbacks:

- *Round Robin (RR)*: this system prevents packet collisions by assigning non-overlapping time intervals to transmissions of nodes that may interfere with each other. As the bitrate of the acoustic links is extremely low, and the low propagation speed of sound requires long guard intervals between transmissions, nodes in an RR system can transmit approximately one packet every 9 s (the time frame is divided into 5 time slots as the packet duration is 1.3 s and a guard time of 0.5 s is used to prevent collisions due to propagation delay and to account for time synchronization errors).
- *ALOHA*: in this scheme, sensors can send up to one packet every 3 s, but risk destructive interference in case of overlapping transmissions by in-range nodes. In order to reduce the risk of collisions, an initial random back-off time of up to one second is used by each node before each transmission. This scheme relies on the relative rarity of shark sightings, since at most 2 sensors from the same cluster can detect the same shark at the same time, excluding the cluster head (which never transmits over the underwater acoustic interface).

Since the tracking system is limited both by the low bitrate offered by the acoustic links and by the limited scanning speed of the sonar, we do not consider complex tracking models for the shark, but rather a simple dead reckoning: as every point between 400 m and 650 m from the coast is covered by at least one sensor, we assume that the shark will continue on the last reported course until an update is received, updating the estimated position once every second. However, as packet losses are relatively frequent, determining whether the shark left the coverage area or multiple packets were just lost is crucial. If the last sensor detecting the shark was on the first or last row, and the shark is not detected for more than 20 seconds, the system assumes that the target is out of range, updating the alarm accordingly. Hence, if the last sensor detecting the shark was at the edge closest to the shore, the alarm level is raised to the maximum, evacuating water users; instead, if the shark was last seen at the outer edge of the coverage area, the alarm is set to 0.

III. Evaluation Scenario and SWAN Performance

We have tested the warning system with the DESERT Underwater network simulator, using real performance figures for the modems. We have only considered instances with a single shark, assuming that there will be no spurious detections due to other large fish or dolphins [4] and that the presumably rare scenario in which multiple sharks simultaneously approach the shore will not occur. The description of how the packet



(a) RR. (b) ALOHA. (c) Ideal communications.

Fig. 3: Confusion matrices for the different communication configurations of the SWAN.

delivery ratio is computed depending on the communication range and on the interference is presented in [15].

As no short-term shark movement models are present in the literature, we assume that the target moves according to a random waypoint model in the overall simulation area. We consider zero standing time, and we model the speed with a Gaussian distribution with mean and standard deviation equal to 2.5 and 1 m/s, according to the estimate of the sustained swimming speed of dangerous shark species [6], [7]. The model represents the motion of a shark that may swim in a direction for some time, and then swiftly changes direction towards a school of fish or another object that captures its interest. While the validation for this model in the literature is limited, as most works tend to concentrate on long-term migration patterns rather than extremely short-term behavior, it represents a good benchmark to evaluate our system: sharks have rarely been observed determinedly moving toward the shoreline, but rather follow prey for a certain distance, then change direction and swim parallel to or away from the shoreline.

We then focus on the alarm function shown in Fig. 2: namely, we consider the difference between the reported alarm level and the correct one, i.e., what an ideal shark spotting system with human observers and perfect visibility would report. As discussed above, we consider Type I and II errors separately, as they have significantly different effects on water users' safety, and consider both the continuous and the quantized version of the alarm level function.

To assess the SWAN performance, we perform 10 different runs for a total of about 3 hours of simulation time. We use the alarm function to compare RR and ALOHA, adding an ideal system as a benchmark: this is an upper bound to the actual performance, as any communication system needs to deal with delay or packet loss. Showing the ideal performance allows us to gauge how much of the error is due to communication impairments and to the slow pace of the sonar, which is the only source of error in the ideal case.

We can first consider the confusion matrix[1] for the quantized alarm function, which shows the types of errors that each of the considered systems makes. Fig. 3 shows the three confusion matrices, with increasing alarm levels from 0 (no shark detected) to 1 (a shark is in the high risk area): the types of scenarios in which the shark evades the tracking are relatively similar, and often include instances in which it moves close to either edge of the area covered by the sensors. We can note that the ALOHA system has a better discrimination performance than RR: the values on the diagonal of the confusion matrix are higher in Fig. 3b than in Fig. 3a, and larger errors are rarer. Errors are also more common at higher alarm levels, as the alarm function is non-linear, and the regions corresponding to higher alarm levels are smaller. However, there is still a significant gap with respect to the upper bound represented by a system with ideal communication, shown in Fig. 3c: in the latter, the alarm level estimate is almost perfect, as updates are frequent and never lost. The high packet loss of underwater acoustic links, along with the difficulty in coordinating between sensors, results in a higher error, but the system can successfully detect a shark approximately 90% of the time, and Type I errors are more frequent than Type II errors, indicating that even with imperfect communications, the system achieves high detection performance and a significant level of safety.

We can also examine the continuous alarm level function to get a better idea of the system's behavior and the conditions in which errors happen. In Fig. 4, we plot the error in the risk factor estimated by the system for a simulation period of 4000 seconds, assigning positive and negative values to the Type I and Type II errors, respectively. Negative values then mean that the system is underestimating the threat posed by the shark, while positive errors mean that it is overestimating it. Most of the time, the system succeeds in estimating the shark trajectory and the tracking error is almost zero. However, there are some periods in which the RR system completely loses track of the

[1] In a confusion matrix for a prediction model, the (i, j)-th entry is the probability that a ground truth value i is predicted as j.

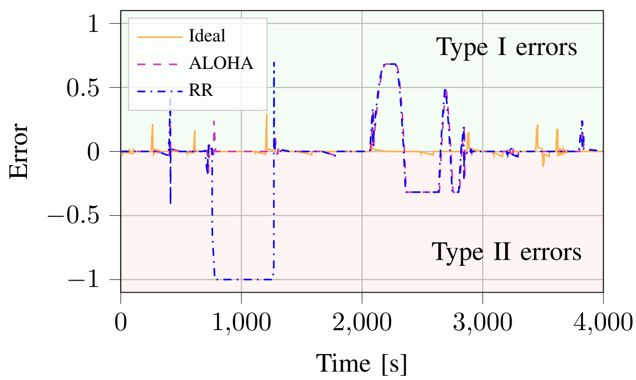


Fig. 4: Tracking error over time. Positive values indicate Type I errors, while negative values indicate Type II errors.

shark: this is caused by the relatively slow pace of RR updates, which can cause the system to miss the shark entirely if just a couple of packets are lost. If the shark traverses the whole area covered by the sensors and moves into the high risk area close to the shore, as shown around the 1000 s mark in the figure, the RR system might miss it entirely and still report that there are no sharks in the area. The ALOHA system avoids this issue, thanks to the faster pace of packet updates: this comes at the cost of a certain risk of collision, but the overall performance of the system is greatly improved. In some cases, both systems can have significant Type I errors, but this type of error has less serious consequences on the safety of water users, as it leads to excessive precautions being taken.

Finally, Fig. 5 shows the Complementary Cumulative Distrbution Function (CCDF) of Type I and Type II errors: ALOHA has a slight advantage over RR. Type I errors occur approximately 26% of the time with all three systems, while Type II errors are rarer, occurring 17.6% of the time for the ALOHA system and 18.2% of the time for RR, while the ideal system only has Type II errors 9% of the time. We can see that ALOHA is slightly better at tracking the shark than RR, while there is a significant gap with the ideal system. However, significant errors are still rare: large Type II errors, in which the shark enters the high risk area undetected, represent approximately 20% of overall Type II errors, i.e., approximately 3.2% for ALOHA and 3.6% for RR. Large Type I errors occur slightly more frequently, but as we mentioned above, they are less dangerous for water user safety.

IV. Conclusions and Future Work

In this paper, we have illustrated the possible design of an automated shark detection and warning system, with several advantages over existing shark-spotting programs: the fully automated nature of the system and its relative robustness to sea conditions, along with the low operating costs, make it a viable alternative to more invasive systems such as drumlines. We show that properly configuring the network and using the most effective access mechanism has a significant effect on performance, and that using an ALOHA system in which only nodes that sense a shark in the vicinity transmit gives the best results with respect to scheduled mechanisms. However, ALOHA is also less robust in scenarios in which more than one shark approaches the shore at the same time, at a distance between 100 and 200 m: this case is presumably rare, but it would lead to a significantly higher risk of interference, which is entirely avoided by an RR system, and we plan to consider it in future work, along with prioritized systems that privilege information on sharks closer to the shore, i.e., more dangerous ones. Other potential research directions on the subject include a field test of the system in a real underwater acoustic network, as well as a tighter collaboration with marine biologists to improve our understanding of shark behavior and threat levels.

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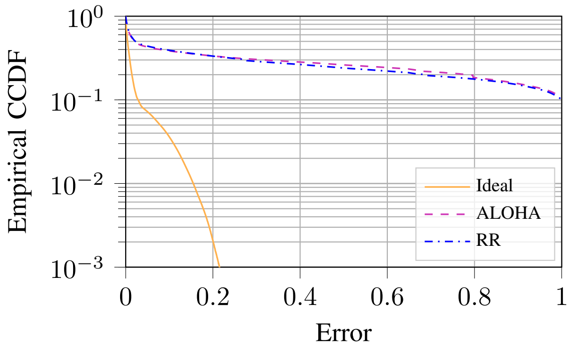
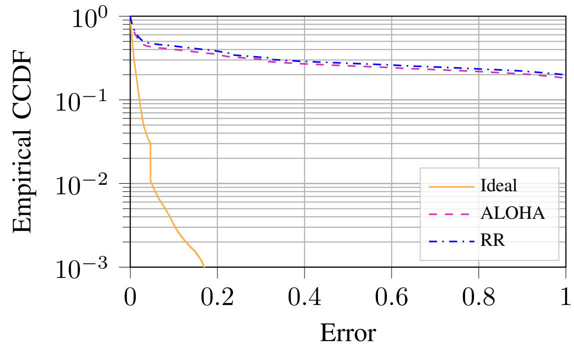


(a) Type I errors.



(b) Type II errors.

Fig. 5: Complementary CDF of the magnitude of the error in both directions.

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