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Initial Development of the Hybrid Aerial Underwater Robotic System (HAUCS): Internet of Things (IoT) for Aquaculture Farms

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***Abstract*— Aquaculture, especially fish farming, plays a vital role in ensuring food security in the United States and worldwide. However, for fish farming to be sustainable and economically viable, drastic improvements to current labor-intensive and resource-inefficient operations are required. The Hybrid Aerial/Underwater RobotiC System (HAUCS) aims to bring fundamental innovations to how pond-based farms operate. HAUCS is an end-to-end framework that consists of three principal subsystems: a team of collaborative aero-amphibious robotic sensing platforms integrated with water quality sensors; a land-based home station that can provide automated charging and sensor cleaning; and a backend processing center that includes a machine-learning-based water quality prediction model and farm control center. HAUCS will be capable of collaborative monitoring and decision-making on farms of varying scales. The HAUCS platform, payload, and prediction model are discussed. The initial deployment of the HAUCS framework at a land-based aquaculture fish farm is presented.**

***Index Terms*— Internet of Things, robotics, machine learning, aquaculture, coastal zone monitoring, water quality sensors**

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I. Introduction

Precision agriculture (PA) is the application of robotic field machines and information technology in agriculture, which plays an increasingly important role in farm production. PA related robotic technology has been an active research topic and has seen robust growth [1-3]. By the United States Department of Agriculture (USDA) estimation, between 1998 and 2013, three key PA technologies saw adoption rates ranging from 25% to 50%: global positioning system (GPS) yield and soil monitors/maps, variable-rate input application technologies, and GPS guidance systems [4]. Many PA applications call for multiple collaborative robots [5, 6], which are closely related to multi-robot persistent coverage problems (MRPCP) [1].

The Internet of Things (IoT) has been adopted to improve productivity and efficiency in agriculture [8]. Aquaculture farming is an important, fast-growing sector of agriculture that has seen the application of advanced technologies such as robotics and IoT [9-21].

IoT solutions have been adopted to realize automated feeding on fish farms to reduce waste and avoid water pollution from the excessive feed. In computer-vision based automatic feeder designs [12, 15], videos are streamed via Bluetooth to a control center where the fish feeding behavior is analyzed to determine the degree of hunger, which controls feeder operation. While such a system might be viable for a small-scale fish tank, it would be challenging to scale up to a fish farm with numerous larger ponds (e.g., >2 hectares). To this end, eFishery is a more realistic IoT-based fish feeder system [10]. The eFishery system is essentially an enhancement demand feeder [20]. One novel design in eFishery is that a vibration sensor is adopted to detect fish activity near the feeder. The sensor data is sent back to the control center for analysis to determine the degree of hunger in the pond, which controls the operation of the feeder. Every feeding event initiated by the feeder is recorded automatically to allow the farm to monitor feed expenses.

In aquaculture fish farming, the management of water quality, particularly dissolved oxygen (DO), is critically important for successful operation. DO depletion is a leading cause of fish mortality on farms. Catastrophic loss can occur within hours if ponds are not appropriately managed. The current management practice on pond-based farms is the use of human operators who drive trucks or other all-terrain vehicles throughout the

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day, but especially at night, to sample and monitor DO in each pond (Fig. 1a). The associated labor and equipment costs limit the scope and frequency of such sampling since dozens of ponds must be managed by each sensor-equipped truck. Large farms require multiple drivers and sampling instruments to attain the required monitoring frequency for proper management. The level of resolution that this approach can achieve on any pond is generally restricted to a single near-shore measurement at a point on the pond with a well-maintained roadbed. On large ponds (e.g., 2 to 8 hectares), this may result in a failure to promptly identify localized water quality problems that can ultimately affect a large proportion of the stock. Even though readings should be taken hourly on each pond, very large farms (>400 hectares) with hundreds of ponds, may only be able to take readings at much lower frequencies due to the labor and equipment costs of operating large fleets of monitoring vehicles. Measurements of additional water quality parameters cannot be performed due to the demanding schedules required of drivers to achieve the minimum frequency for DO management. Furthermore, with the current practice, operators have a very limited window of time (e.g., less than an hour in the middle of the night) to react to potential oxygen depletion, increasing the potential likelihood of catastrophic events. The response (e.g., putting emergency aeration equipment in a pond) takes time away from achieving DO measurement frequencies.

(a) (b)

Fig. 1. Illustrations of (a) Truck-based sampling (photo courtesy of Pete Reiff, Logan Hollow Fish Farm), (b) Aquaculture Pond Buoy from In-Situ Inc. [2]

There have been attempts to reduce labor costs by automating aquaculture pond monitoring, such as the Aquaculture Pond Buoy from In-Situ Inc. [21] (Fig. 1b). Other IoT water quality monitoring solutions include Neer Yantra from PranisCOM [11, 19] and PondGuard from Eruvaka [13]. These and many other solutions employ buoy-based monitoring stations [14,16-18] that measure pond-water quality parameters such as DO, temperature, pH, etc. Sensor data can be sent via WiFi or cellular link to a control center for analysis. However, these stationary instruments deployed in the water are difficult to maintain due to biofouling. They can be cost-prohibitive since individual stations are required for each site measured in a pond. Stationary instruments suffer from the same limitation as truck-based monitoring since only a single location is monitored unless multiple expensive sensor buoys are deployed in each pond. In addition, sensor buoys are an obstruction in the pond during harvest as they must be removed or lifted over the seine. The advantage they offer is a high-frequency sampling. Many proposed solutions do not adequately consider the challenge of data connectivity on fish farms at various scales.

The **H**ybrid **A**erial/**U**nderwater Roboti**C** **S**ystem (HAUCS) framework aims to mitigate the aforementioned issues to provide automated, high-density monitoring of key environmental metrics of each aquaculture pond on a farm using relatively inexpensive robotic sensing platforms.

With support from the National Institute of Food and Agriculture (NIFA), USDA through the Ubiquitous Collaborative Robots (NRI-2.0) program, the HAUCS project was launched in the Spring of 2019. The development mainly focused on three areas deemed to be of higher priority: the development and deployment of an automated system based on the HAUCS concept on our research partner farm – Logan Hollow Fish Farm, machine learning (ML)-based DO prediction model development, and the HAUCS AUP design.

This paper aims to introduce the HAUCS framework. We also present the initial HAUCS development effort. In Section II, we discuss the overall HAUCS concept. In Section III, we provide some detailed system design considerations. We present our initial experimental results in Section IV and conclusions in Section V.

II. The HAUCS System Concept

A. Overview of the HAUCS Framework

HAUCS is a framework that aims to achieve collaborative monitoring and decision-making on aquaculture farms of varying scales. The "collaboration" will be among robotic systems, machines, and human operators.

HAUCS consists of the following subsystems: a team of collaborative aero-amphibious robotic sensing platforms capable of in-air and on-water movement, integrated with underwater sensors; land-based infrastructure, such as weather stations and home stations that provide automated charging and sensor cleaning; and backend modeling and processing infrastructure. The backend processing center consists of an ML-based water quality prediction model and a farm control center. A LoRa [22] communication network is employed to connect the different components in HAUCS. The communication hub may also be integrated with land-based components to overcome obstacles, such as treelines.

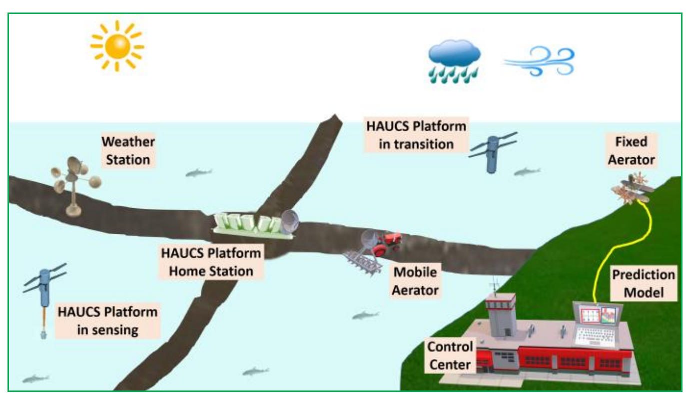

Fig. 2. A Basic HAUCS concept of operations

Each HAUCS autonomous unmanned platform (AUP) consists of an unmanned robotic vehicle and submerged underwater sensors. The robotic vehicle will be an aero-amphibious platform that can travel on the water surface and fly in the air. The platform will provide all-weather coverage capabilities important for farm monitoring operations, especially in high-wind conditions. The HAUCS AUPs will cover the entire farm in a reasonable period with high location precision. Data from the lightweight underwater sensors attached to the vehicle, such as DO sensors, will be sent to the farm control center via a radio link during sensing operations. An ML-based data analytics engine will analyze the sensor data to predict pond conditions at the backend. Sensor data from all the ponds on the farm and the associated weather data will be used to train the prediction model. The model prediction will, in turn, change the behavior of the HAUCS AUPs (i.e., increasing/decreasing patrolling frequency) or control other instruments to mitigate an emergency situation (e.g., turning on fixed aerator or instructing human operators to move mobile emergency aeration equipment into place in a pond).

This highly scalable framework will convert aquaculture farm operations to an "Internet of Aquaculture." The design can be easily scaled up to a multi-farm framework, where a data center gathers sensor data from all the farms for analysis and prediction. The overall concept of operations is illustrated in Figure 2.

The overarching goal of HAUCS is to relieve human operators from the most labor-intensive, time-consuming, and expensive operations in aquaculture farming operations through a group of cooperative robotic sensing and actuator platforms. HAUCS will conduct automated sampling at frequencies relevant for accurate prediction of water quality variation (e.g., hourly diel readings), providing significant advantages in speed, cost, resource efficiency, and adaptability over the traditional manual and truck-mounted water quality measurement systems. Compared with many other IoT solutions, HAUCS provides the following advantages:

- Improved scalability – capable of collaborative monitoring and decision-making on farms of varying scales.
- More accurate reporting of pond conditions – capable of sampling multiple locations in the pond to monitor spatial and temporal pond variations.
- Mitigated biofouling – avoiding maintaining sensors in bio-productive water.
- Broad coverage – novel sensing patterns can be realized to cover different areas on a large pond.

B. HAUCS Autonomous Unmanned Platform

The HAUCS sensing platform will need to meet several challenges. First, the design will need to be power-efficient so that each platform can cover multiple ponds on an hourly basis under all weather conditions. Second, the sensor maintenance will need to be easy since one serious drawback of the state-of-art Aquaculture Pond Buoy is a challenge associated with sensor maintenance. Third, the system will need to be low cost to be acceptable in the aquaculture farm industry. Lastly, the platform will have to maintain a communication link with the control center to send sensor data promptly for accurate monitoring of the overall farm.

To meet these challenges, a group of mobile robotic sensing platforms will be employed. The AUP will be integrated with lightweight sensors (i.e., a DO sensor may weigh about 50g [23]). The platform will move through the pond in the air or on the water during sensing operations, dependent on weather conditions, and return to the land base. A payload extension module will be integrated with the platform so that the sensors will be underwater only during the sensing operation. Another major advantage is biofouling reduction and simplified sensor maintenance. Platform home/maintenance stations will be constructed at several different locations across the farm; each station will be assigned a coverage area (e.g., 100 ponds). The station will host the HAUCS robotic platforms that will monitor these ponds, reducing the traffic on the farm. These platforms will return to their assigned home station, where automatic sensor cleaning can be performed during charging. The home stations will also serve as communication hubs. A team of mobile robotic sensing platforms covering multiple ponds will offer significant cost reductions.

Several different types of unmanned platforms have been evaluated as candidates in the HAUCS design. While each of these platforms offers some advantages, they all have deficiencies. Commercial off-the-shelf (COTS) aerial drones have become increasingly affordable and offer increased range and payload capacity. However, one fundamental limitation of these drones is their ability to operate under challenging weather conditions, especially in high wind. Unmanned surface vehicles (USVs) can operate under all-weather conditions. The USVs also provide broader spatial coverage of the pond. Unfortunately, the USVs will have similar issues to those that plagued the stationary sensor buoy: biofouling, maintenance difficulties, and per-pond installation expenses.

Table 1. Comparison of different platform options.

	Cost	**Speed**	**Maintenance**	**All-Weather**
Aerial Drone	Low	Fast	Easy	High Wind
Unmanned Surface Vehicle	High (one platform per pond)	Medium	Hard (biofouling)	Good
Stationary Sensors	High (one platform per pond)	Fast	Hard (biofouling)	Good
Human Boom Truck	High (labor and vehicle)	Slow	Easy	Good

Through these analyses, it is clear that we will need to develop HAUCS platforms capable of aero-amphibious (air, water) movements to satisfy mission requirements. In normal weather conditions, HAUCS AUP will operate as an aerial drone to efficiently cover more ponds. However, the AUP will be capable of operating as a USV to help mitigate severe weather conditions such as strong wind. In particular, a sail-driven USV will be attractive. In such a design, the wind can help to power the AUP instead of impeding the operation of the platform. In a related project, a sail-driven small-waterplane-area twin-hull (SWATH) platform is being investigated at the Department of Ocean and Mechanical Engineering at FAU as an unmanned Arctic scientific research vessel [24]. With automated sailing to provide its propulsive power and soft solar panel coated sail, the vessel is designed to be self-sustaining. As the SWATH sails over the Arctic Ocean, its twin underwater turbines generate energy for mission support when it encounters the local current.

C. HAUCS AUP Sensing Scheme

As discussed in Section I, one deficiency of buoy-based sensor stations is the lack of spatial coverage that can be achieved. Pond conditions may vary substantially at different locations in the same pond. Spatial and temporal variations of water quality

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parameters in three 0.4-hectare aquaculture ponds were investigated [25]. It was concluded that locations within the pond were the highest source of variability. Spatial locations contribute to 75% of the variance of particulate carbon (PC), particulate nitrogen (PN), and 35% of the variance of total dissolved phosphorus (TDP). While DO was not tracked in this study, the result for TDP can be regarded as a proxy for DO due to the high correlation between TDP and DO. The contribution to the measurement variances from different locations can be expected to be even higher for large ponds (e.g., 2 to 8 hectares). This motivated the recent investigation of three-dimensional short-term DO spatial distributions [26]. A combination of fixed sensor installations and measurements using handheld sensors at various locations in one pond were utilized in this study.

The HAUCS framework, for the first time, will enable novel sensing schemes that cover extended spatial regions and provide more robust readings than traditional truck-based or buoy-based data collection processes. For example, to acquire DO sensor data, the sensor will need to be in contact with the water body for about 30 seconds [7]. A potential scheme will be that when the platform first enters a new pond, the platform will be stationary at one location for up to 30 seconds before moving through the pond toward an adjacent pond. During the process, the sensor will stay in contact with the water body to collect a stream of water quality data (Fig. 3). This sensing scheme will effectively use the transition time to acquire significantly more data samples and capture the spatial variability of water quality in a pond.

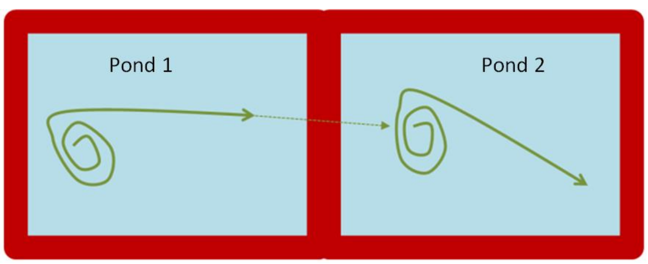

Fig. 3. Illustration of the mobile platform-based sensing scheme

Another advantage of the agility of the HAUCS sensing platform is that the sensing scheme (i.e., sampling patterns, frequencies, areas of focus, etc.) can adapt to environmental and pond conditions. Such adaptations may be the result of the prediction model or weather changes detected by weather stations on the farm.

D. HAUCS Communication Link

Central to the HAUCS design will be a need to ensure robust and flexible communication among HAUCS platforms, home stations, weather stations, and the control center, which will serve as the data aggregation hub. Coverage must reach the whole farm, which can be large. For example, one of the large catfish farms - Tackett Catfish Farm at Greenwood, MS [29], has a span of 8km. While achieving long-distance communication, wireless transceiver must consume very little power to ensure operational longevity. Fortunately, given that the data to be collected is relatively low-dimensional and low-rate, the technology need not be high-bandwidth.

These requirements are well aligned with LoRa standards [22] and the latest LoRa chipsets from Appcon Wireless technology [27], Semtech [28], and others. LoRa chipsets rely on chirp spread spectrum modulation in an unlicensed sub-GHz band (e.g., 915MHz). The latest radios are inexpensive (e.g., <$50), achieve very long distances (e.g., >30km line-of-sight), and consume very little power during transmission (e.g., 10mW). Given the relatively flat topography and limited land-cover of commercial aquaculture farms, these chipsets are expected to perform exceedingly well in the target environments. Additional gateway nodes can be installed at strategic locations throughout the farm to ensure farm-wide connectivity. Furthermore, should communication faults arise, transmission limitations can be recognized in situ, triggering a rise in elevation by the HAUCS platform, establishing an improved line-of-sight to a LoRa hub.

The communication network must provide robust operation in the presence of failures at multiple hubs (e.g., due to a lightning storm). This will be achieved by over-provisioning LoRa gateway nodes (i.e., multiple communication hubs), potentially in concert with the adoption of LoRaWAN, which automates the handling of overlapping reception regions and duplicate packet elimination. In this model, messages are received by all in-range gateways, with duplicate elimination performed upstream. Failed gateways are simply ignored until they are rebooted or replaced, with no significant impact on the system's operation.

E. Machine Learning Farm Condition Prediction Model

An ML prediction model will be adopted for farm pond condition prediction in the HAUCS framework. The primary focus will be the accurate prediction of DO concentration in each pond – the keystone pond health indicator in intensive aquaculture management. In the seminal work of Boyd et al. [30], a simple graphical technique was adopted to use DO measurements made at dusk and in the early evening hours to predict DO concentration during the night and at dawn. This technique is still widely adopted on many fish farms and will be employed to provide reference predictions due to its broad adoption. However, the Boyd model does not consider many other environmental factors such as temperature, wind speed, wind direction, etc., due to the highly nonlinear relationships between the DO concentration and these factors. Various ML techniques, such as artificial neural networks (ANNs), have been adopted to develop more accurate DO concentration prediction models [31-33]. The motivation is that ANNs can better abstract (or learn) the mathematical models of a complex ecological system such as a fish pond on an aquaculture farm. A least-squares support vector machine (LSSVM) was adopted in their prediction model in the studies by Juan et al. [33]. While LSSVM offers some benefit over SVM regarding training speed, the lack of sparseness and robustness may reduce the prediction accuracy for real data sets [54]. The Back Propagation technique adopted in [32] has the problem of being sensitive to outliers. Another issue with all these techniques is that the models were validated with single pond data. Even though it was mentioned that monitoring was conducted on 120 river crab farms in [31], the analysis seemed to be conducted on one pond.

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The overall architecture of the proposed hybrid DO prediction model in HAUCS is shown in Fig. 4. A Long Short-Term Memory (LSTM) [35] based recurrent neural network (RNN) is adopted. LSTM can provide better preservation of long-range dependencies in time series prediction.

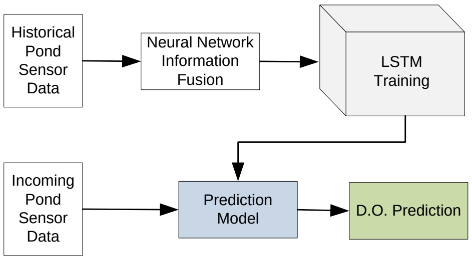

Fig. 4. Hybrid NN-LSTM DO prediction model

However, one challenge with LSTM networks is that they do not work well with incomplete data (i.e., gaps in the time series data). Unfortunately, incomplete data and missing data can be expected to occur in the field due to interference from various sources. To address this issue, a novel solution is adopted to train a feedforward neural network (FNN)to learn the patterns of the ponds and to predict the missing values. The structure of the missing DO value prediction network is shown in Fig. 5. The input layer includes vectors of the pond ID, time of day, weather, and a bias. The hidden layer is constructed with sigmoid functions, and the output layer produces the missing DO value for a specific pond at a specific time of day.

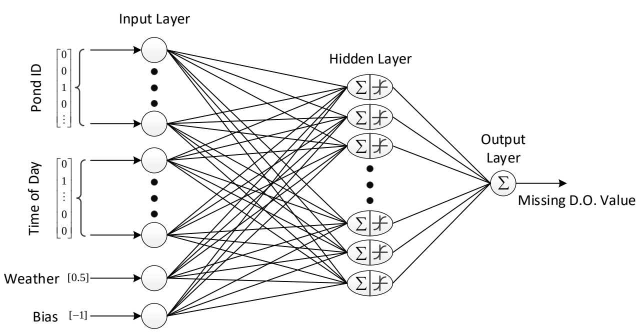

Fig. 5. Multilayer FNN for Missing DO value prediction

The LSTM network is then trained using the fused dataset, pond by pond. A bias is introduced to reduce false negatives (i.e., predicting a higher than actual DO level) by scoring them with higher error than false-positive predictions. This induces the LSTM network to make conservative predictions, avoiding predictions higher than the actual DO level. The target function is the prediction error regularized by the $L2$ norm of all trainable weights, shown in the following equation:

$$\sum_{t=1}^{T}\|y_t-\hat{y}_t\|+\alpha\sum_{t=1}^{\tilde{T}}\|y_t^{'}-\hat{y}_t^{'}\|+\beta\|W\| \quad (1)$$

where the first term in the objective function represents the prediction error of all the training samples, in which y_t and $\hat{y}_t$ are the ground truth and the predicted value at time $t\in T$; the second term in the objective function represents the false-negative prediction error, in which $y_t^{'}$ and $\hat{y}_t^{'}$ are the ground truth and the predicted value with false-negative prediction at time $t\in\tilde{T}$, $\tilde{T}$ is the total samples that are with false-negative predictions, and α is the penalty factor for false-negative; and the third term in the objective function denotes the weights of all neural networks in the proposed model, in which β is the trade-off coefficient for the regularizer. The ML model will predict the pond status using the sensor data from the team of HAUCS AUPs and other environmental data such as temperatures, wind speeds, and wind directions from the weather stations as inputs. The training of the ML model can be conducted offline, separate from the normal farm control operations. The ML model can also be trained online (i.e., using incremental learning) with new sensor measurements and weather data.

F. HAUCS Mission Control and Path Planning

We are presenting our current effort on developing a generic baseline algorithm here. A detailed report of the HAUCS mission control and path planning algorithm development will be published in our future work.

The mission control and path planning algorithm in the HAUCS framework is crucial to achieving the coordination among the HAUCS AUPs to provide persistent, accurate, and up-to-date situational awareness and to collaborate with the human operators to accomplish farm water quality control. The mission control will have to meet several challenges:

- Reaction to a pond in distress by increasing its patrolling frequency and dispatching mobile emergency aerators to that pond.
- Hybrid movements and flight mode transitions to adapt to terrain and weather.
- Capable of avoiding obstacles at fixed locations (e.g., fixed aerators) and moving obstacles (e.g., mobile emergency aerators or human-operated vehicles).

A baseline algorithm based on a hybrid control system has been developed to control and regulate the HAUCS framework. The architecture of the hybrid controller is shown in Fig 6. This includes a central server, operators, and individual AUPs assigned for each segment of the farm.

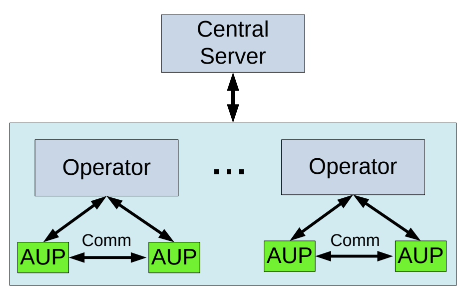

Fig. 6. Hybrid Control Architecture

The goal of HAUCS mission control is to provide path plans and maintain the traffic of deployed AUPs within the context of unmanned aerial system (UAS) traffic management. The central server in the control architecture provides information about weather and distress calls from ponds to the operators. The server also tracks and monitors the movement of AUPs in the deployed region to make sure that their paths do not intersect. Both the central server and operators can exchange information. Each server is connected to multiple operators.

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The operators perform flight/path planning procedures and send instructions to the AUPs. The AUPs communicate with each other and operate in a decentralized manner. The HAUCS AUPs are assumed to be homogeneous. Each HAUCS AUP will be assigned to a home station and operate in a known environment with unpredicted variables (e.g., weather, moving obstacles, and pond conditions).

Generally, the path planning methods provide the path for the individual AUP to complete the mission under certain environmental conditions. The environment can be categorized as static or dynamic. Path planning in a static environment assumes no moving obstacles, and the trajectory of the agent to its destination is predetermined. In a dynamic environment, which may include moving obstacles or neighboring AUPs/agents, there is a need for dynamic path planning techniques [55].

The path planning algorithms that can be used for HAUCS should organize agents (i.e., AUPs) spatially and take decisions in a cooperative fashion [56]. Specifically, they include coverage algorithms, task allocation protocols, and motion planning algorithms. Coverage Path Planning (CPP) algorithms determine the optimal route of an AUP to cover a desired area or space while avoiding obstacles. The algorithms also consider environmental conditions such as weather changes. The agents are instructed to make continuous and sequential movements without overlapping their paths. CPP is generally used in mapping, crop monitoring, and land assessment [57]. Approaches to CPP are categorized as randomized and complete. A randomized approach does not consider the geographical information of the farm and, therefore, takes a long time to cover the whole area. On the contrary, in a complete approach, the coverage area is decomposed into cellular regions, and an optimal path is traversed to cover all the cells (i.e., ponds). Details about cellular decomposition and optimal path searching can be found in [58, 59].

In the first phase of the work, the operator generates an optimal path plan for the AUP to cover a target area using the rotating calipers algorithm [65, 66]. The farm is defined as a convex polygon, $P=(V, E)$, where $V=\{1,\dots, n\}$ is the set of vertices of a polygon, and $E=\{(1,2), \dots, (n,1)\}$ is the set of edges. The starting/takeoff location and ending/landing location of the AUP is defined as x_s and x_e. The idea is to generate a back and forth flight pattern with waypoints, $W=(x_0, \dots, x_m)$ to cover the polygon. The final path includes x_s and x_e along with the waypoints, $Z=(x_s, x_0, \dots, x_m, x_e)$ as shown in Fig. 7. The path is shown by a blue line from start location to end location. The whole farm is split into four ponds (polygons) by the red color intersection lines.

In a convex polygon, a line passing through the vertex such that the whole polygon lies on one side of the line is called a line of support. The pair of vertices that admit parallel lines of support are called antipodal pairs. The waypoint generation requires the computation of all pairs of antipodal points on the surface of the polygon. The algorithm then finds the best path for each antipodal pair. The best path is the one with the least back and forth flight lines, corresponding to the minimum width of the polygon. The algorithm selects the path having the lowest cost, with a computational complexity of O(n). The later stages of the path planning can be broadly posed as:

- Area assignment of AUPs to cover the fish farm.
- Coverage planning of AUPs in cooperative fashion.

Finding the minimum number of vehicles to cover a region has been solved in [67] using an optimization approach. The anchored area partition problem has been discussed in [68] that facilitates coverage of a larger region by multiple vehicles. This would enable the AUPs to cover a larger region cooperatively.

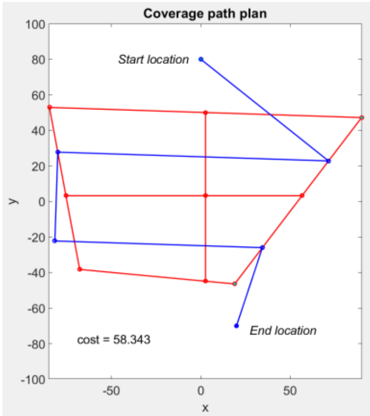

Fig 7. A sample path plan over four ponds

Other partitioning strategies can also be adopted for the initial assignment of different subgraphs (i.e., ponds) to each HAUCS AUP using offline Multilevel Subgraph Patrolling (MSP), a multilevel partitioning algorithm [36]. For routine operations, the distributed Greedy Bayesian Strategy (GBS) scheme [37] is being investigated due to its excellent scalability, critical for large fish farms.

Collision avoidance is critical in any path planning procedure. Artificial Potential Functions (APF) are a set of algorithms frequently used to navigate autonomous agents [60,61]. This method uses the concept of potential functions from magnetic and electric fields. Here, each vehicle or agent is taken as a point charge in space that gets attracted or repelled from nearby agents based on their distance. This results in a push/pull dynamic between agents. The attractive or repulsive force, typically defined as the negative gradient of a suitable potential function, is applied to each agent. Applications of APF can be found in path planning [60] and task allocation [61]. APF algorithms have high scalability and low bandwidth use [56].

The Traveling Salesman Problem (TSP) is a task allocation algorithm that generates an optimal path for an AUP to travel across some target locations with a minimum cost. It is an NP-hard problem in combinatorial optimization. If the AUPs have limited energy and limited weight carrying capacity, characterized as a Vehicle Routing Problem (VRP). Present applications of TSP/VRP algorithms are in package delivery and data collection [57].

Geofencing is a recent method of path planning that has found applications in UAS traffic management. In geofencing, airspace is divided into several zones used by an individual AUP or team of AUPs. This system is designed for traffic management across the growing number of AUPs in the airspace. Some scenarios of interacting geofences for

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multi-stage flight plans have been detailed in [62]. A geofencing based path planner is presented in [63]. Bio-inspired algorithms like Ant Colony Optimization are proposed in [64] for farmland monitoring.

An adaptive approach to path planning of AUPs will also be investigated. The flight mode changes can be handled by location-based waypoints assignments: *sampling waypoints* (i.e., moving within the same pond) and *transition waypoints* (i.e., moving to a different pond or its home station on land). The control center will maintain the third type of waypoint – *protective waypoints* to cope with severe weather. For example, upon detecting the potential for strong winds, the control center can update the waypoints to protective waypoints to allow the HAUCS AUPs to take evasive action such as operating as USVs. The control center can restore the waypoint status at a later time when conditions return to normal.

The handling of the automatic emergency response will be centralized at the control center. Following the same logic of keeping emergency mobile aerators prepared for the potentially distressed ponds, each home station will store additional HAUCS AUPs as reserves. Once the prediction model detects a stressed pond, an automatic emergency response process will be invoked. The networked fixed aerators can be turned on; field operators may also be instructed to move the mobile emergency aerator in place. Escalation procedures will be in place to allow human intervention when all mobile aerators are in use. The patrolling frequency of the pond in distress will be increased by releasing the reserve AUPs to join the regular AUP. When the model detects that the distress is relieved, the aerators can be automatically switched off by the control center – critical for cost and energy reduction. The mobile aerators will be available to handle other emergencies, and reserve HAUCS AUPs will return to their home stations.

G. Land-based HAUCS Subsystems

In addition to the mobile platforms, the HAUCS framework will comprise land-based fixed installations. Environmental conditions, such as wind speed, direction, rainfall, etc., are needed in the DO prediction model and are also essential for the operation of the HAUCS platforms. Weather stations will be installed at strategic locations on the farm and integrated through the LoRa link. To improve the efficiency of HAUCS sensing platforms, automated maintenance home stations will be installed at various locations throughout the farm. These stations will fulfill the following tasks: a) automatic platform charging; b) automatic sensor maintenance (e.g., spraying fresh water, with an inexpensive wiper system integrated within the charging dock); and (3) serving as a communication hub when needed.

With regard to home station deployment strategies, our initial plan will be to adopt the simplest solution: uniformly partitioning the farm into different operating zones and deploy one home station at the center of each zone. Alternatively, the home station placement can be formulated as an optimization problem to minimize the total energy cost, subject to constraints such as the terrain and size of the farm, range limits of the LoRa links, weather conditions, etc. Therefore, the mission control and path planning algorithms discussed above will be highly relevant. In particular, the approach of interacting geofences for a multilayer partitioning discussed in [62] will be investigated.

Automated charging is another critical aspect of HAUCS. Commercially available outdoor drone charging stations, such as the Heisha C200 outdoor charging pad [38], are being explored. The latest progress in wireless phone charging solutions will also being investigated. In particular, the Qi wireless charging standard is being extended to support medium power (i.e., 65w to 200w) devices [39], which will be a viable solution for HAUCS. We will focus on automated charging solutions after the HAUCS AUP design becomes more mature and publish the results in our future work.

III. The Current Development status of haucs

A. HAUCS AUP development

Multiple drone configurations were evaluated as the foundation to develop the amphibious HAUCS AUPs. Two alternatives were investigated in addition to the quadcopter: Ornithopter (flapping wing) drones and vertical takeoff and land (VTOL) platforms. The ornithopter concept has drawn interest from both the Defense Advanced Research Projects Agency (DARPA) and US Army Research Lab (ARL) for the potential to withstand strong winds. However, most current ornithopter designs aim at micro-form-factors with minimum payloads.

One type of VTOL platform – the coaxial-rotor-copter drone or coaxial drone, has drawn our attention. Instead of employing a tail rotor to balance the yaw moments as in the single rotor copter, coaxial drones use two contra-rotating rotors to compensate for each other's torque. The coaxial drone has been adopted in the Mars Helicopter design for NASA's 2020 Mars Rover mission [40]. The "Gun Launched Micro Air Vehicle" proposed in [41] was an early compact coaxial drone design. In 2015, Ascent Aerosystems commercialized a similar compact design – the Sprite drone. Ascent has since moved into the area of industrial and military-grade drones with their rugged Spirit drone [42]. Several open-source designs similar to the Sprite drone, such as the TDrone [43] and the Navi [44], are available.

For the HAUCS framework, the coaxial drone has some intrinsic advantages over the quadcopter. The lightweight design, coupled with the lower transmission and shaft power losses, provides a useful load advantage over the multi-rotor configuration. The moment of inertia of a coaxial drone is lower than that of a quadcopter since its center of gravity is closer to the concentric line of the rotor shaft. In turn, the lower moment of inertia helps increase the platform's controllability and maneuverability [45]. The TDrone/Sprite design provides additional attractive features – the drone body is very compact and can be easily made water-tight. It is easy to integrate different payloads into the main body.

For these reasons, the coaxial drone has been adopted as the initial baseline HAUCS AUP. One drawback of the Tdrone/Sprite design is that the swashplate-based steering and driving mechanism are complex. Thus, the thrust vectoring coaxial drone is adopted in HAUCS AUP design, inspired by several open-source thrust vectoring coaxial drone concepts [47- 49].

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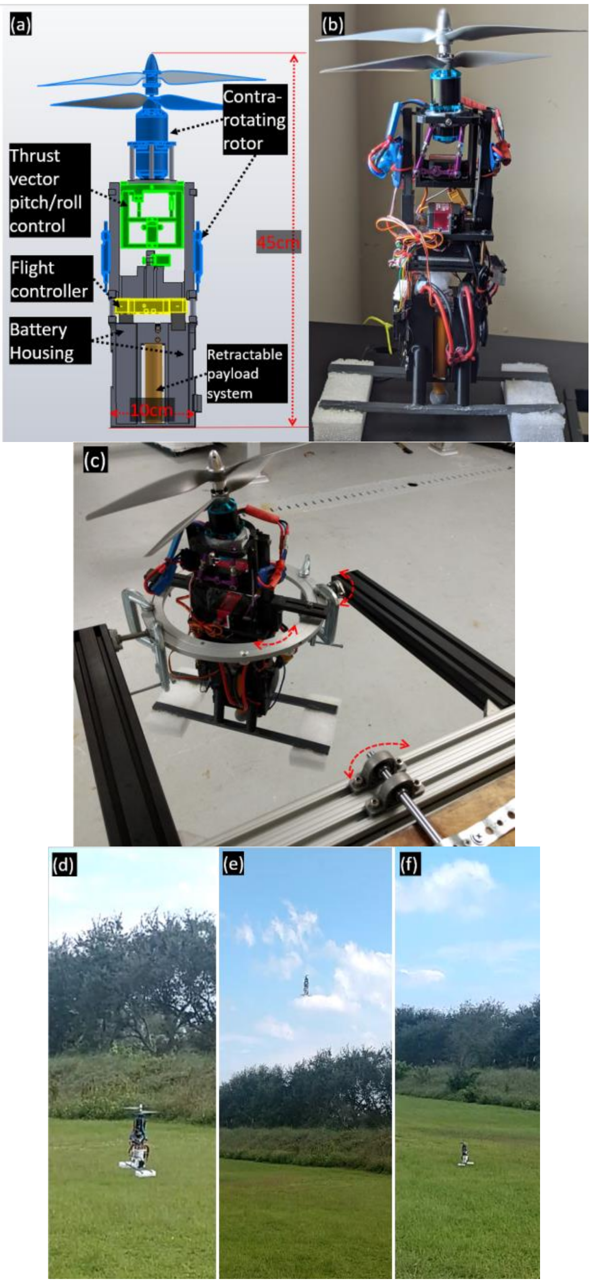


Fig. 8. Illustration of the thrust vector coaxial drone using contra-rotation rotor and a gimbal. (a) Prototype under development at SAIL/HBOI. (b) The prototype under development at SAIL/HBOI (additional accessories include GPS module, radio receiver, and safety switch). (c) A gimbal stand is used to evaluate the pitch, roll, and yaw of the platform. (d-f) Video frames to illustrate the drone test in the open field: (d) drone taking off, (e) drone in-flight, and (f) drone landing.

A prototype based on the thrust vectoring coaxial drone concept is currently under development at the System and Imaging laboratory (SAIL) at HBOI/FAU. As highlighted in the CAD rendering in Fig 8a, the driving mechanism is provided by one contra-rotating rotor. The steering mechanism is accomplished by a gimbal controlled by two servos – a significantly more simplified mechanism than the TDrone. The prototype has a diameter of 10cm and a length of 45cm. The electronic control module is implemented using off-the-shelf components (Fig 8b). For flight control, the open-source Ardupilot [50] is loaded onto a compact Pixhawk PX4 PIX 2.4.8 Flight Controller. A Himax CR3516-1030 Contra Rotating Outrunner brushless motor is used in the prototype, connected to the flight controller via the RC Electric Parts 40A RC Brushless Motor Electric Speed Controller (ESC). Steering control is accomplished through the two servos connected to the pitch and roll rings. To support the platform development, a gimbal harness was constructed. The six-degree of freedom movements allowed by this harness ensures the drone's pitch, roll, and yaw can be tested non-destructively on the stand (Fig. 8c). This harness allowed us to promptly identify potential issues in the platform structure and the flight controller software and speed up the development process. The coaxial drone was successfully demonstrated through flight tests in the open field. (Fig. 8d-f).

It is worth mentioning that unmanned aerial vehicles have been employed in aquatic environmental and ecology studies. For example, the Pelican drone developed at the Delft University of Technology can land on the water to fetch water samples back to the lab for analysis [51]. However, significant energy will be required for the platforms to take off from the water surface. Therefore, such a design may not be desirable for long-endurance surveillance missions.

Consequently, an important design consideration is to reduce the *unnecessary* contact area between the platform and the water body during operation to reduce energy consumption. Accordingly, the HAUCS AUP design employs a retractable payload extension. The payload extension will allow the instrument to penetrate the water surface during sensing and be retracted during the flight, as illustrated in Fig. 9.

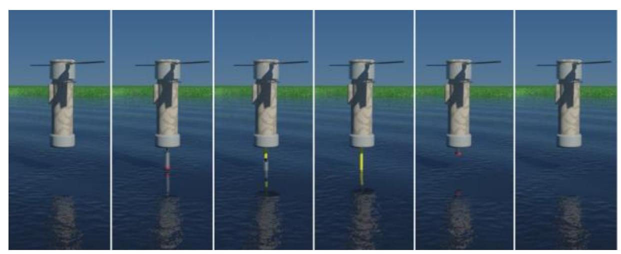
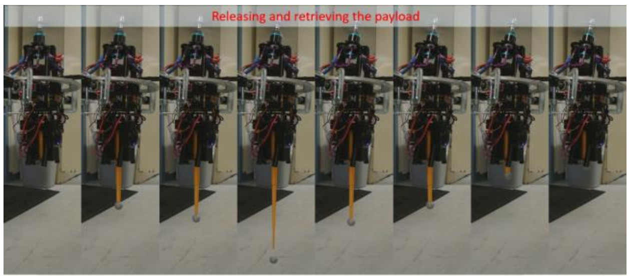


Fig. 9. Illustration of the HAUCS sensing operating using a retractable payload extension

A rigid payload extension is adopted to improve the controllability of both the depth and the direction of the attached sensors. Direction control will be crucial for electro-optical sensors such as underwater cameras that may be adopted for future tasks. The payload extension design is inspired by devices such as telescopic retractable straws or retractable fishing rod. The module consists of a series of nested tapered tubes, which rely on the sensor weight to extend and lock the rods in place. A micro winch is used to retrieve the rods and the instrument.

A payload extension prototype has been developed as a proof-of-concept (Fig. 10a). The prototype consists of five sections. The length of each section is 10cm. The total extended length is 45cm. Since the mounting base is inside the frame (Fig 8a), the actual extension outside of the frame is 35cm. A dummy sensor was used while the DO and temperature sensors are being finalized. During deployment, a (full rotation) servo lowers the rods to form a rigid extension. To retrieve the module, the servo is operated in reverse. Multiple payload release and retrieval trials were performed successfully in the HBOI SAIL lab to validate the payload extension module design (Fig. 10b). While the current extension is relatively short, these laboratory tests showed that the nested, tapered, tube-based design is sound.

(a) Payload extension prototype in retracted and extended mode



(b) A sequence of video frames showing the AUP platform hovering in flight to operate the payload extension module

Fig. 10. Illustration of payload extension module and the AUP in action in a laboratory environment

B. *Initial Deployment on the Farm*

To validate the HAUCS concept, an automated sensing system has been developed and deployed on our research partner farm – Logan Hollow Fish Farm, located in southwest Illinois in the bottomland of the Mississippi River.

Fig. 11. (a) The installations of the DO and temperature sensors and the LoRa antennas on the farm truck. (b) The sensor and LoRa shields on the Arduino Uno board (c) The PC stick connected with the Arduino Uno to provide local storage and WiFi access to the mobile DAQ unit.

The prototype consists of a mobile data acquisition (DAQ) subsystem and a farm control center. Both the mobile unit and the data processing unit are built on the Arduino Uno board. With the HAUCS AUP under development at HBOI-FAU, the mobile DAQ unit was integrated with one of the DO monitoring trucks employed on the farm. The HBOI DO, and temperature sensors were mounted side-by-side with the farm's own DO sensor. The LoRa antenna was mounted on a pole at the back of the truck (Fig. 11a). The mobile DAQ unit consisted of DO and temperature sensor shields, a GPS shield for positioning information, and a LoRa shield to stream data to the farm data processing unit (Fig 11b). The Arduino board was connected to a PC stick that logged the data locally (Fig 11c). The PC stick could be accessed via the WiFi link when the truck returned to the office area during breaks, providing the ability to troubleshoot the mobile DAQ unit remotely.

The control center's LoRa antenna was mounted on the farm office's rooftop, 10 meters off the ground (Fig. 12a). A TV amplifier was used to boost the signal. The control center was located in the farm manager's office (Fig 12b). This initial control center consisted of a LoRa shield on an Arduino Uno board to receive the data from the mobile unit (Fig 12c). The Arduino board was connected to a PC stick (Fig. 12d). The sensor data was stored in the control center unit after necessary data quality control, such as removing redundant measurements and associating data with the correct pond using the GPS location information. The data could then be fetched to a remote server and fed into the prediction model.

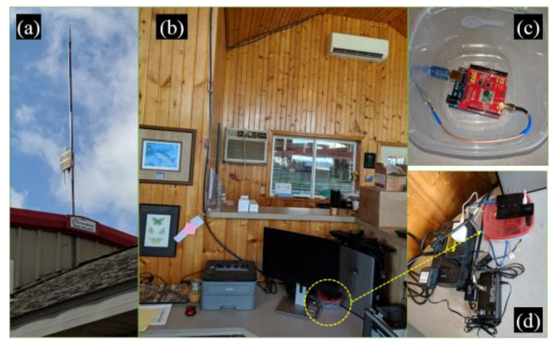


Fig. 12. (a) LoRa antenna for the data processing unit on the rooftop of the farm manager office. (b) Data processing unit inside the farm manager's office. (c) The LoRa shield and the Arduino Uno board for the data processing unit (d) The data processing unit PC stick for data quality control and storage.

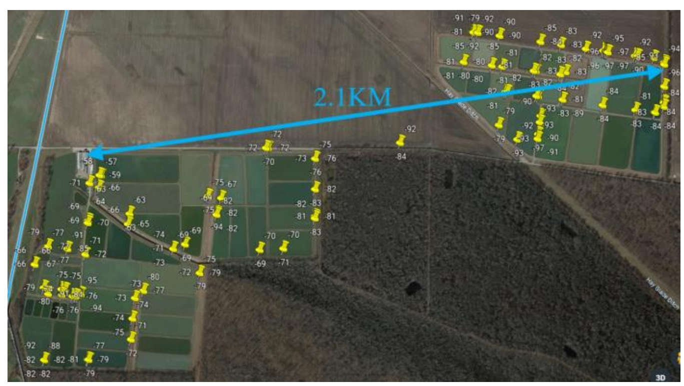


Fig. 13. LoRa signal heatmap of Logan Hollow Fish Farm measured on 9/3/2019. The pins indicated a successful link between the mobile unit and the control center. The numbers indicated the signal strength.

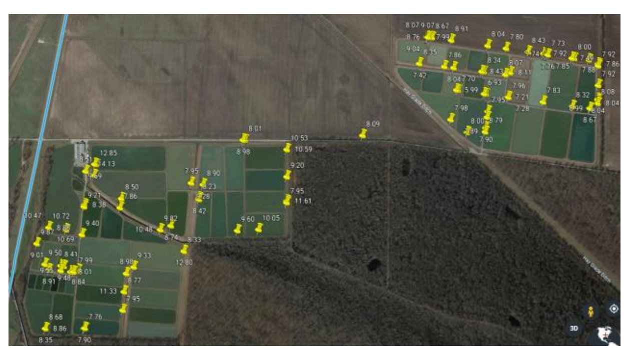


Fig. 14. DO data collected on 9/3/2019 during the field data acquisition experiments using the automated system.

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The system was deployed on Logan Hollow Farm during September and October 2019. The distance between the office and the furthermost pond is 2.12 KM. The LoRa heat map of the farm on 9/3/2019 is shown in Fig 13. There was no coverage in one strip (the marked area) where the treelines blocked the line of sight to the farm office. Data from the ponds adjacent to this strip were collected by deploying sensors at different sections of these ponds (Fig.14).

While this system is only an interim step before implementing robotic sensing platforms, it helped the team gain firsthand experience of the LoRa network in the fish farm environment. More importantly, this system provides the farm with the tangible benefit of adopting an automated data acquisition system. This helps to reduce the barriers to the acceptance of robotic technology by the fish farmers. It is also worth pointing out that, while it is preliminary, the integration of the truck-based automated DO data acquisition with the HAUCS prediction model can have a direct and transformative impact on the fish farm operations.

C. ML Prediction Model Development

The effectiveness of the proposed prediction model was first validated using the high temporal-resolution dataset from the HBOI Indian River Lagoon (IRL) land/ocean biogeochemical observatory (LOBO) [52]. The LOBO DO sensor data for August 2018 was used in the study. The DO prediction result is shown in Fig. 15.

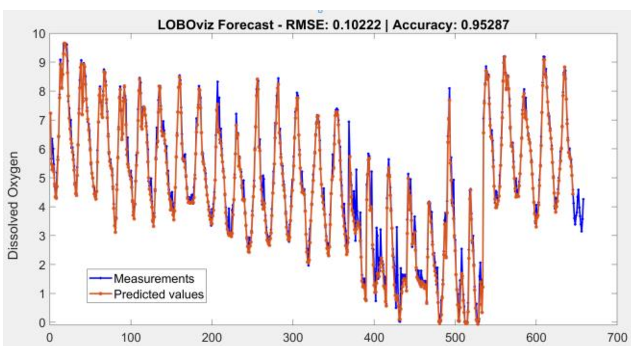

Fig. 15. Performance of the LSTM DO prediction model for the LOBO dataset. The penalty term enables the model to provide more conservative predictions.

The red curve represents the model predictions at each point in time, and the blue curve represents the actual measured data. It can be observed from the figure that the prediction values match well with the measurements, and the prediction results are stable. In this LSTM model, the algorithm has been tuned to bias the prediction toward a lower bound to avoid false negatives. The figure verifies the effectiveness of employing a penalty term to reduce the probability that the prediction is lower than the actual data (i.e., predicting a normal DO level when the actual DO level will go below the threshold).

The machine-learning-based prediction model was then applied to the fish pond development dataset, which consists of the DO data manually collected from 65 ponds on Logan Hollow Fish Farm for one month. Fig. 16 demonstrates the missing DO value predictions using the proposed structure based on a multilayer FNN.

Simulations were conducted to validate the effectiveness of the FNN in predicting the missing pond measurements. During the simulations, varying percentages of data (12%-28%) were randomly removed from a complete dataset. Fifty trials were conducted for each case. As shown in the box plot in Fig. 16a, the mean squared error (MSE) of the predicted values remained low. Fig. 16b shows the raw measurements, where "NaNs" represent the missing data points, and Fig. 16c demonstrates the FNN-predicted data points that can be used for LSTM training and prediction.

(a) Simulations to illustrate the effectiveness of the FNN in predicting the missing data in the pond measurement data

(b)

12	16.0	13.0	11.6	9.8	8.6	8.0
13	11.8	11.6	10.6	10.0	9.4	8.4
14	16.0	13.0	10.2	8.4	5.8	6.0
15	12.2	11.4	10.6	8.2	6.6	5.8
16	6.2	8.6	7.4	6.8	5.2	4.6
17	16.0	13.2	11.4	10.2	5.4	7.8
18	7.8	7.0	4.6	6.0	**NaN**	5.6
19	10.4	9.8	9.0	8.4	**NaN**	6.8
20	11.4	11.0	10.6	9.4	**NaN**	7.6
21	6.2	6.0	5.8	5.4	**NaN**	4.6
22	7.8	8.2	7.6	7.0	**NaN**	6.0
23	7.8	8.0	7.4	6.8	**NaN**	5.8
24	16.0	13.2	11.8	10.6	**NaN**	8.4
25	8.8	8.6	7.6	6.8	**NaN**	5.4
26	7.8	8.2	7.4	6.8	**NaN**	5.2
27	11.0	10.8	9.6	8.8	7.8	6.4

(c)

12	16.0	13.0	11.6	9.8	8.6	8.0
13	11.8	11.6	10.6	10.0	9.4	8.4
14	16.0	13.0	10.2	8.4	5.8	6.0
15	12.2	11.4	10.6	8.2	6.6	5.8
16	6.2	8.6	7.4	6.8	5.2	4.6
17	16.0	13.2	11.4	10.2	5.4	7.8
18	7.8	7.0	4.6	6.0	**5.0**	5.6
19	10.4	9.8	9.0	8.4	**6.8**	6.8
20	11.4	11.0	10.6	9.4	**8.0**	7.6
21	6.2	6.0	5.8	5.4	**3.4**	4.6
22	7.8	8.2	7.6	7.0	**5.2**	6.0
23	7.8	8.0	7.4	6.8	**5.0**	5.8
24	16.0	13.2	11.8	10.6	**10.0**	8.4
25	8.8	8.6	7.6	6.8	**5.3**	5.4
26	7.8	8.2	7.4	6.8	**4.9**	5.2
27	11.0	10.8	9.6	8.8	7.8	6.4

Fig. 16. Missing DO value predictions using the proposed structure. (b) and (c) illustrate the missing DO measurements and the corresponding FNN predicted values.

To quantify the model performance, we have used the root-mean-squared error (RMSE) and the mean absolute percentage error (MAPE) as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{2}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{3}$$

$$Accuracy = 1 - MAPE \tag{4}$$

where y_i and $\hat{y}_i$ are observed, and predicted data, respectively, and N is the total number of predictions. All the respective time series data sets are scaled into the range of [0,1] to be used for sigmoid units in the neural network and LSTM models.

The DO prediction performance for four typical ponds (pond 26, 52, 13, and 44) are shown in Fig. 17. The results of ponds 26 and 52 (Fig. 17a and 17b) showed very effective and accurate predictions, where the RMSE values were very low.

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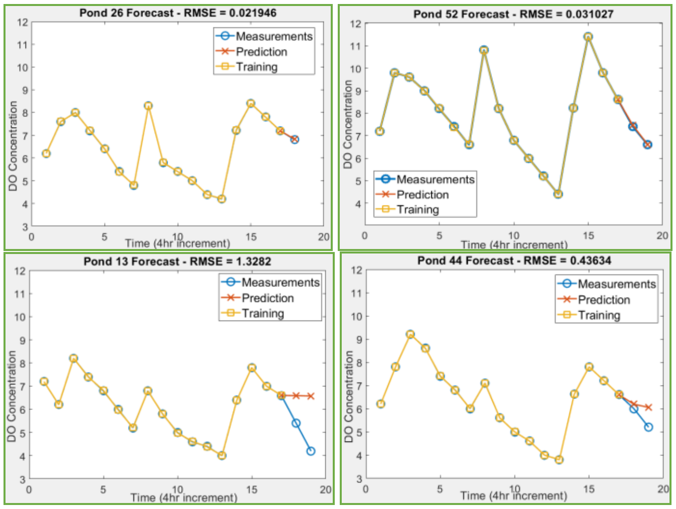


Fig. 17. Detailed performance of the Hybrid NN-LSTM DO prediction model for typical pond 26, 52, 13, and 44.

It is worth noting that the predictions for pond 26 were four-hour-look-ahead, and the predictions for pond 52 were eight-hour-look-ahead. The four-hour-look-ahead predictions for ponds 13 and 44 (Fig. 17c and 17d) were less satisfying. One possible reason for the degraded performance might be that human interventions are not fully integrated into our model training. For example, if the DO in a pond fell below a specific level (i.e., 4), aerators could be turned on to bring the DO back to the desired level. We will take these activities and other systemic factors into account in model training in future work.

The four-hour-look-ahead MAPE of all the ponds is shown in Fig. 18. The prediction accuracy of the worst pond was **78%**. The average accuracy was **92%**. The accuracy achieved with our current prediction model is unmatched by the existing empirical formula based technique.

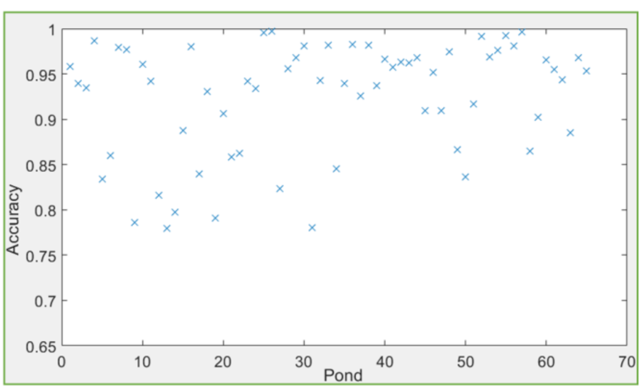
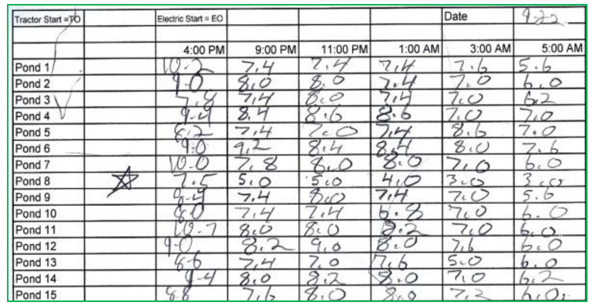


Fig. 18. Performance of the model for 4-hour-look-ahead of all the ponds.

D. Comparison between HAUCS and the State-of-the-Art

The development of the HAUCS system and deployment of the initial truck-based sensor system has led to significant improvement in fidelity of data collection that will improve farm water quality management. The current "state-of-the-art" data collection system being deployed on the farm without these improvements is crude and fraught with potential decision-making problems (e.g., transcription issues and paucity of data collected) (Fig 19). Our truck based deployment eliminates the transcription and data storage issues plaguing the paper-based system.



Tractor Start = TO		Electric Start = EO				Date	9-22
		4:00 PM	9:00 PM	11:00 PM	1:00 AM	3:00 AM	5:00 AM
Pond 1		10.2	7.4	7.4	7.4	7.6	5.6
Pond 2		9.0	8.0	8.0	7.4	7.0	6.0
Pond 3		7.8	7.4	8.0	7.4	7.0	6.2
Pond 4		9.4	8.4	8.6	8.6	7.0	7.0
Pond 5		8.2	7.4	7.0	7.4	8.6	7.0
Pond 6		9.0	9.2	8.4	8.4	8.0	7.6
Pond 7		10.0	7.8	8.0	8.0	7.0	6.0
Pond 8		7.5	5.0	5.0	4.0	3.0	3.0
Pond 9		9.4	7.4	8.0	7.4	7.0	5.6
Pond 10		8.0	7.4	7.4	6.8	7.0	6.0
Pond 11		10.7	8.0	8.0	8.2	7.0	6.0
Pond 12		9.0	8.2	9.0	8.0	7.6	6.0
Pond 13		6.6	7.4	7.0	7.6	5.0	6.0
Pond 14		9.4	8.0	8.2	8.0	7.0	6.2
Pond 15		8.8	7.6	8.0	8.0	7.2	6.0

Fig. 19. Example hand-written dissolved oxygen datasheet for "state-of-the-art" sampling method deployed on an operating fish farm.

The "state-of-the-art" data collection and truck-based system provides data collection frequencies of once every 2 hours per pond and typically only measurement site per pond. The HAUCS will allow multiple measurement sites per pond and the ability to collect transect data to incorporate within pond variability into predictions (Fig. 2). Depending upon the number of drones deployed, the HAUCS system will manage one visit per hour, halving the time between visits. Ponds predicted to be low in DO concentration will be visited at a higher frequency if needed. Those predicted to have sufficient oxygen can be visited less frequently, allowing for optimization of fleet deployment. This is less practical for the truck-based system since the trucks follow a predetermined route that is restricted by the quality of the levee roads (i.e., not all levees have all-weather roads) and the deployment of the sensor boom toward only the left side of the vehicle.

Table 2. Estimated annual cost (US $) comparison between the "State-of-the-art" truck-based system and the HAUCS system for small and large farms.

	"State-of-the-art"		HAUCS	
	Small Farm	**Large Farm**	**Small Farm**	**Large Farm**
Ponds (#)	80	1000	80	1000
sample rate (Ponds*hr^{-1}*vehicle^{-1})	40	40	10	10
Truck/Drone* ($ ea/year)	5000	5000	400	400
Number needed	2	24	8	100
DO meter* ($ ea/year)	240	240	120	120
Number needed	2	24	8	100
Base Station* ($ ea/year)	-	-	200	400
Number needed	-	-	2	24
Home Station* ($ ea/year)	-	-	200	200
Number needed	-	-	1	2
Fuel/Electricity ($ per vehicle/year)	2063	2063	9	9
Personnel Salary ($/year @$15/hr)	31320	31320	31320	31320
Personnel Fringe ($/year)	9396	9396	9396	9396
Staff (#/year)	3	34	3	14
Total Cost of Operation ($/year)	75679	867432	65303	337876
Savings ($/year)			**10376**	**529556**
Savings per pond ($/year)			**130**	**530**
* Assume five-year service life for vehicles, meters, base and home stations				

A comprehensive cost comparison is outside the scope of this paper. However, a simplified analysis that includes vehicle and personnel time suggests that the HAUCS system could save a small farm (80 ponds) about $10K per year and a large farm (1000 ponds) $530K per year when costs are normalized to one reading per pond per hour (Table 2). This amounts to an estimated annual savings of $130 per pond and $530 per pond for small and large farms, respectively, assuming no livestock loss under any of the scenarios. The truck operators have the

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dual tasks of measurement and moving and turning on aerators using the manual system. Alternatively, with the HAUCS system, the operators will be substantially relieved of the measurement task.

IV. Conclusion

In this paper, the concept of the Hybrid Aerial Underwater Robotic System (HAUCS) has been introduced. HAUCS is a transformative IoT solution that aims to achieve collaborative monitoring and decision-making on aquaculture farms of varying scales through the collaboration of amphibious robotic platforms, land-based infrastructure, processing algorithms, and human operators. HAUCS overcomes many drawbacks in existing state-of-the-art aquaculture fish farm monitoring solutions, namely, the lack of sufficient spatial coverage of the ponds, sensors that are susceptible to biofouling, high deployment costs, and maintenance difficulties.

HAUCS is a versatile system. In addition to fish farm water quality monitoring, the HAUCS framework can easily be extended and adapted for other environmental monitoring applications such as coastal zone surveillance. The integration of the payload extension will enable HAUCS AUPs to conduct missions in an energy-efficient way.

The coaxial-rotor based prototype demonstrated great potential as the foundation of the HAUCS AUP. Extending the aerial platforms to a sail-driven USV will provide HAUCS AUP the all-weather capability and transform wind from an impediment to an energy source to power the AUP when operating in USV mode.

The initial truck-based automated sensing system validated the HUACS concept and provided a practical environmental monitoring alternative that is vastly more robust and effective than the current practice.

This LSTM-FNN hybrid network-based DO prediction model has performed very well. Against the datasets from the Logan Hollow fish farm, it achieved an average accuracy of 92%. It is noteworthy that this model is robust again data gaps that can occur in the field due to interference from various sources. This work, therefore, laid a solid foundation to develop more sophisticated ML-based prediction models.

As we advance, one of the future research foci will be to develop the amphibious HAUCS AUP and validate the performance with our collaborator – Logan Hollow Fish Farm. Developing land-based infrastructures, especially the automated charging solution, will also be another key area. The availability of the HAUCS AUPs will enable the investigation of different sensing schemes to optimize the spatial coverage of the ponds. This will, in turn, enable us to extend the DO prediction model from simple pond-based time series prediction to a more robust multidimensional prediction of DO distribution across ponds. In addition, navigating through the Federal Aviation Administration (FAA) regulatory framework for multiple-drone operation and nighttime operation will be essential for real-world deployment of the HAUCS system.

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References

[1] A. Srinvasan, *Handbook of Precision Agriculture: Principles and Applications.* Boca Raton, FL, USA: CRC Press, 2006.

[2] S. Bhandari, A. Raheja, R. L. Green and D. Do, "Towards collaboration between unmanned aerial and ground vehicles for precision agriculture," in *Proc. SPIE 10218 Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping II*, 2017, doi: 10.1117/12.2262049.

[3] F. Cheein, D. Herrera, J. Gimenez, R. Carelli, M. Torres-Torriti, J. R. Rosell-Polo, A. Escolà and J. Arnó, "Human-robot interaction in precision agriculture: Sharing the workspace with service units," in *IEEE Intl. Conf. Ind. Tech. (ICIT)*, 2015, pp.289-295, doi: 10.1109/ICIT.2015.7125113.

[4] D. Schimmelpfennig, *Precision agriculture technologies, and factors affecting their adoption*, 2016, [online]. Available: https://www.ers.usda.gov/amber-waves/2016/december/precision-agriculture-technologies-and-factors-affecting-their-adoption/.

[5] P. Tokekar, J. V. Hook, D. Mulla and V. Isler, "Sensor planning for a Symbiotic UAV and UGV system for precision agriculture," *IEEE Trans. Robot.* , vol. 32, no. 6, pp. 1498-1511, 2016, doi: 10.1109/TRO.2016.2603528.

[6] K. R. Aravind, P. Raja and M. Pérez-Ruiz, "Task-based agricultural mobile robots in arable farming: A review," *Span. J. Ag. Res.*, vol. 15, no. 1, pp. 1-16, 2017, doi: 10.5424/sjar/2017151-9573.

[7] N. Michael, E. Stump and K. Mohta, "Persistent surveillance with a team of MAVs," in *2011 IEEE/RSJ Intl. Conf. Int. Rob. Syst., (IROS)*, pp. 2708-2716, 2011, doi: 10.1109/IROS.2011.6095174.

[8] O. Elijah, T. Abdul Rahman, I. Orikumhi, C. Y. Leow and N. Hindia, "An overview of the Internet of Things (IoT) and data analytics in agriculture: Benefits and challenges," *IEEE Internet Things J.*, vol. 5, no. 5, pp. 3758 - 3773, 2018, doi: 10.1109/JIOT.2018.2844296.

[9] *YSI Professional Plus User Manual*, 2020 [online]. Available: https://www.ysi.com/File%20Library/Documents/Manuals/605596-YSI-ProPlus-User-Manual-RevD.pdf.

[10] J. Anderson, 2015, *Fish Farm Feeder Dispenses Feed based on Fish Hunger Levels*, [online]. Available: https://newatlas.com/efishery-fish-farm-smart-feeder/39940/.

[11] *8 digital technologies disrupting aquaculture*, 2017, [online]. Available: https://www.alltech.com/blog/8-digital-technologies-disrupting-aquaculture.

[12] M. M. Alammar and A. Al-Ataby. *An intelligent approach of the fish feeding system.* 2018, [online] Available: https://pdfs.semanticscholar.org/7ac2/c06e915ec669f25c3accaa9f73847fa6a034.pdf.

[13] *Eruvaka*, 2020, [online]. Available: https://eruvaka.com/.

[14] I. Ullah and D. Kim, "An optimization scheme for water pump control in smart fish farm with efficient energy consumption," *Processes*, vol. 6, no. 6, p.65, 2018, doi: 10.3390/pr6060065.

[15] J.-V. Lee, J.-L. Loo, Y.-D. Chuah, P.-Y. Tang, Y.-C. Tan and W.-J. Goh, "The use of vision in a sustainable aquaculture feeding system," *Res. J. Appl. Sci., Eng. Technol.*, vol. 6, no. 19, pp. 3658-3669, 2013, [online] Available from: https://www.researchgate.net/profile/Joo_Loo/publication/267271146_The_Use_Of_Vision_In_a_Sustainable_Aquaculture_Feeding_System/links/5449b6ba0cf244fe9ea60e4c/The-Use-Of-Vision-In-a-Sustainable-Aquaculture-Feeding-System.pdf.

[16] G. Gao, K. Xiao and M. Chen, "An intelligent IoT-based control and traceability system to forecast and maintain water quality in freshwater fish farms," *Comp. Elect. Ag.*, vol. 166, p. 105013, 2019, doi: 10.1016/j.compag.2019.105013.

[17] K. S. Rama Raju and G. Kumar Varma, "Knowledge-based real-time

monitoring system for aquaculture using IoT," in *2017 IEEE 7th Intl. Adv. Comp. Conf. (IACC)*, pp. 318-321, 2017, doi: 10.1109/IACC.2017.0075.
[18] P. Sun and Y. Chen, "Aquiculture remote monitoring system based on Internet of Things," in *2019 Intl. Conf. Robots Intel. Syst. (ICRIS)*, pp. 187-190, IEEE, 2019, doi: 10.1109/IACC.2017.0075.
[19] *Our pond monitoring system Neer Yantra improves productivity and yield in aquaculture farming initiative*, 2019, [online] Available: http://www.praniscomtech.com/2019/09/26/our-pond-monitoring-system-neer-yantra-improves-productivity-and-yield-in-aquaculture-farming-initiative.
[20] D. P. Statler, "Use of self-feeders for rearing steelhead trout at Dworshak National Fish Hatchery," *Prog. Fish-Cult.*, vol. 44, no. 4, p. 195, 1982, doi: 10.1577/1548-8659(1982)44[195:UOSFRS]2.0.CO;2.
[21] *Aquaculture buoy with RDO® Titan Probe*, 2020, [online]. Available: https://in-situ.com/us/products/aquaculture/aquaculture-pond-buoy.
[22] *LoRaWAN™, What is it?*, 2015., [online] Available: https://lora-alliance.org/sites/default/files/2018-04/what-is-lorawan.pdf.
[23] *Dissolved Oxygen Sensors*, 2020, [online] Available: https://www.idronaut.it/sensors/polarographic-oxygen-sensor/.
[24] *Literature survey and the conceptual design of an unmanned arctic ocean scientific vessel*, 2018 [online] Available: http://fau.digital.flvc.org/islandora/object/fau%3A40896.
[25] L. S. Wei and A. E. Laws, "Spatial and temporal variation of water column measurements in aquaculture ponds," *Aquacult.*, vol. 78, no. 3–4, pp. 253-266, 1989, doi: 10.1016/0044-8486(89)90103-8.
[26] Y. Chen, H. Yu, Y. Cheng and Q. Che, "A hybrid intelligent method for threedimensional short-term prediction of dissolved oxygen content in aquaculture," PLoS ONE, vol. 13, no. 2, p. e0192456, 2018, doi: 10.1371/journal.pone.0192456.
[27] *Lora Module: Ultra long range RF1276, February 12, 2018*, 2018, [online] Available: http://www.appconwireless.com/uploadfile/RF1276.pdf.
[28] *Migrating an Internet of Things (IoT) Sensor Design to LoRaWAN*, 2020, [online] Available: https://info.semtech.com/hubfs/Sensor%20Design%20Conversion%20Process%20WhitePaper_Final.pdf.
[29] *Tackett Catfish Farm*, 2018, [online]. Available: https://www.google.com/maps/place/Tackett+Fish+Farms/@33.547582,-90.4122691,14141a,35y,90h/data=!3m1!1e3!4m5!3m4!1s0x862a443c5586b40b:0x5196a45b5e8880de!8m2!3d33.583334!4d-90.4259444.
[30] C. E. Boyd, R. P. Romaire, and E. Johnston, "Predicting early morning dissolved oxygen concentrations in channel catfish ponds," *Trans. Am. Fish. Soc.*, vol. 107, no. 3, pp. 484-492, 1978, doi: 10.1577/1548-8659(1978)107<484:PEMDOC>2.0.CO;2.
[31] S. Liu, L. Xu, Y. Jiang, D. Li, Y. Chen and Z. Li, "A hybrid WA–CPSO-LSSVR model for dissolved oxygen content," *Eng. App. Art. Int.*, vol. 29, p. 114–124, 2014, doi: 10.1016/j.engappai.2013.09.019.
[32] L. Xu and S. Liu, "Study of short-term water quality prediction model based on wavelet neural network," *Math. Comp. Mod.*, vol. 58, no. 3-4, pp. 807-813, 2013, doi: 10.1016/j.mcm.2012.12.023.
[33] J. Huan, W. Cao and Y. Qin, "Prediction of dissolved oxygen in aquaculture based on EEMD and LSSVM optimized by the Bayesian evidence framework," *Comp. Elect. Ag.*, vol. 150, no. 2018, p. 257–265, 2018, doi: 10.1016/j.compag.2018.04.022.
[34] A. K. Suykens, J. De Brabanter, L. Lukas and J. Vandewalle, "Weighted least squares support vector machines: Robustness and sparse approximation," *Neurocomp.*, vol. 48, no. 1, p. 85–105, 2002, doi: 10.1016/S0925-2312(01)00644-0.
[35] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neur. Comp.*, vol. 9, no. 8, pp. 1735-1780, 1997, doi: 10.1162/neco.1997.9.8.1735.
[36] D. Portugal and R. Rocha, "MSP algorithm: Multi-robot patrolling based on territory allocation using balanced graph partitioning," in *Proc. of Symp. Appl. Comp. (SAC 2010)*, Sierre, Switzerland, 2010, pp. 1271-1276, doi: 10.1145/1774088.1774360.
[37] D. Portugal and R. Rocha, "Distributed multi-robot patrol: A scalable and fault-tolerant framework," *Robot. Auton. Syst.*, vol. 61, no. 12, pp. 1572-1587, 2013, doi: 10.1016/j.robot.2013.06.011.
[38] *Unattended Technology: The Move Towards Greater Drone Automation, June 25, 2019*, 2019, [online] Available: https://dronelife.com/2019/06/25/unattended-technology-the-move-towards-greater-drone-automation/.
[39] *Medium power standard*, 2019, [online] Available https://www.wirelesspowerconsortium.com/medium-power/.
[40] *Mars helicopter a new challenge for flight*, 2019, [online] Available https://www.jpl.nasa.gov/universe/archive/universe1807.pdf.
[41] A. Koehl, H. Rafaralahy, M. Boutayeb, and B. Martinez, "Aerodynamic modeling and experimental identification of a coaxial-rotor UAV," *J. Int. Robot. Syst.*, vol. 68, no. 1, p. 53–68, Sept. 2012, doi: 10.1007/s10846-012-9665-x.
[42] *Spirit*, 2018, [online] Available https://ww.ascentaerosystems.com/spirit.
[43] *TDrone----Open source coaxial drone!*, 2019, [online] Available https://diydrones.com/profiles/blogs/tdrone-open-source-coaxial-drone.
[44] *Hackaday prize entry: coaxial drones*, 2019, [online] Available https://hackaday.com/2017/05/09/hackaday-prize-entry-coaxial-drones/.
[45] L. Chen and P. J. McKerrow, "Modelling the Lama coaxial helicopter," in *Proc. Australasian. Conf. Robot. Autom.*, (Brisbane), 2007, pp. 1-9, [online]. Available: http://ro.uow.edu.au/cgi/viewcontent.cgi?article=1741&context=infopapers.
[46] N. Zhao, H. Deng, C. Wang, K. Li and S. Jia, "Design and dynamic modeling of a coaxial-rotor system," *2016 8th Intel. Conf. Mod. Ident.Cont. (ICMIC)*, Algiers, 2016, pp. 989-994, doi: 10.1109/ICMIC.2016.7804258.
[47] *Thrust Vectoring Design for Ball Drone*, 2012, [online video] Available: https://www.youtube.com/watch?v=CSm-TNPms7E.
[48] *Multiwii dualcopter with thrust vectoring coaxial motors*, 2015, [online video] Available https://www.youtube.com/watch?v=AI4LI4DgiOw.
[49] *Thrust vectoring coaxial drone update, August 14, 2016*, 2019, [online] Available https://diydrones.com/profiles/blogs/thrust-vectoring-coaxial-drone-update.
[50] *Pelican drone ensures super quick water sampling*, 2019, [online] Available http://mavlab.tudelft.nl/2019/09/25.
[51] D. M. Hanisak, K. S. Davis and B. Metzger, "The Indian River Lagoon Observatory: Real-time water quality data network for research, education, outreach," *Sea Tech.*, vol. 56, no. 8, pp. 27-31, Aug. 2015.
[52] D. L. White, S. Esswein, J. O. Hallstrom and C. Post, "The Intelligent River©: Implementation of sensor web enablement technologies across three tiers of system architecture: Fabric, middleware, and application," in *2010 Intl. Symp. Collab.Tech. Syst.*, 2010, pp. 340-348, [online] Available: https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=5478493.
[53] P. Razvan, T. Mikolov and Y. Bengio, "On the difficulty of training recurrent neural networks," in *Proc. 30th Int. Conf. Machine Learning*, 2013, pp. 1310-1318, [online] Available: http://arxiv.org/abs/1211.5063.
[54] Z. Cao, S. Yu, B. Ouyang, F. Dalgleish, A. Vuorenkoski and J. Principe, "Marine animal classification using combined CNN and hand-designed image features," *IEEE J. of Oceanic Eng*, vol. 44, no. 4, pp. 1116 - 1129, 2019, doi: 10.23919/OCEANS.2015.7404375.
[55] B. Mahajan, P. Marbate, "Literature review on path planning in dynamic," in *IJCSN International Journal of Computer Science and Network*, 2013.
[56] F. Rossi, S. Bandyopadhyay, M. Wolf, and M. Pavone, "Review of multi-agent algorithms for collective behavior: a structural taxonomy," *IFAC-PapersOnLine*, 51(12), 112–117, 2018, doi: 10.1016/j.ifacol.2018.07.09.
[57] J. Xie, L. R. G. Carrillo, and L. Jin, "Path planning for UAV to cover multiple separated convex polygonal regions," *IEEE Access*, 1–1, 2020, doi: 10.1109/access.2020.2980203.
[58] E. Galceran and M. Carreras, "A survey on coverage path planning for robotics," *Robotics and Autonomous Systems*, vol. 61, no. 12, pp. 1258–1276, 2013, doi: 10.1016/j.robot.2013.09.004.
[59] H. Choset, "Coverage for robotics-a survey of recent results," *Annals of mathematics and artificial intelligence*, vol. 31, no. 1-4, pp. 113–126, 2001, doi: 10.1023/A:1016639210559.
[60] D. E. Koditschek, and E. Rimon, "Robot navigation functions on manifolds with boundary," *Advances in Applied Mathematics*, 11(4), 412–442, 1990, doi: 10.1016/0196-8858(90)90017-s.
[61] T. Weigel, J.-S. Gutmann, M. Dietl, A. Kleiner, and B. Nebel, "CS Freiburg: coordinating robots for successful soccer playing," *IEEE Transactions on Robotics and Automation*, 18(5), 685–699. doi: 10.1109/tra.2002.804041.
[62] M. N. Stevens, and E. M. Atkins, "Geofencing in immediate reaches airspace for unmanned aircraft system traffic management," *AIAA*

Information Systems-AIAA Infotech@Aerospace, Kissimmee, Florida, 2018, doi: 10.2514/6.2018-2140.

[63] Y. Liu, R. Lv, X. Guan, and J. Zeng, "Path planning for unmanned aerial vehicle under geo-fencing and minimum safe separation constraints," *12th World Congress on Intelligent Control and Automation (WCICA)*, 2016, doi: 10.1109/wcica.2016.7578482.

[64] J. Yang, X. Wang, Z. Li, P. Yang, X. Luo, K. Zhang, S. Zhang, L. Chen, "Path planning of unmanned aerial vehicles for farmland information monitoring based on WSN," *12th World Congress on Intelligent Control and Automation (WCICA)*, Guilin, China, 2016, doi: 10.1109/wcica.2016.7578794.

[65] J. I. Vasquez Gomez, M. M. Melchor and J. C. Herrera Lozada, "Optimal Coverage Path Planning Based on the Rotating Calipers Algorithm," 2017 International Conference on Mechatronics, Electronics and Automotive Engineering (ICMEAE), Cuernavaca, pp. 140-144, 2017, doi: 10.1109/ICMEAE.2017.11.

[66] M. L. Shamos, "Computational Geometry," PhD thesis, Yale University, 1978.

[67] G. Avellar, G. Pereira, L. Pimenta, and P. Iscold, "Multi-UAV Routing for Area Coverage and Remote Sensing with Minimum Time. Sensors, "2015, 15. 27783-27803. 10.3390/s151127783.

[68] I. Maza, and A. Ollero, "Multiple UAV cooperative searching operation using polygon area decomposition and efficient coverage algorithms, "2007, 10.1007/978-4-431-35873-2_22.

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