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Tracking the Fine Scale Movements of Fish using Autonomous Maritime Robotics: A Systematic State of the Art Review

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ABSTRACT

This paper provides a systematic state of the art review on tracking the fine scale movements of fish with the use of autonomous maritime robotics. Knowledge of migration patterns and the localisation of specific species of fish at a given time is vital to many aspects of conservation. This paper reviews these technologies and provides insight into what systems are being used and why. The review results show that a larger amount of complex systems that use a deep learning techniques are used over more simplistic approaches to the design. Most results found in the study involve Autonomous Underwater Vehicles, which generally require the most complex array of sensors. The results also provide insight into future research such as methods involving swarm intelligence, which has seen an increase in use in recent years. This synthesis of current and future research will be helpful to research teams working to create an autonomous vehicle with intentions to track, navigate or survey.

1. Introduction

Determining the patterns of fish migration and the causes of their migration is critical to scientific studies both for the ecology of any given environment, but also in the development of management plans for conservation or sustainable exploitation (Anras and Lagardère, 2004). Tracking the distance and time of fish movement is fundamental to understanding why fish have certain behaviours (Hilborn and Walters, 2013). This allows researchers to accurately simulate the predicted reactions of the fish to changes that are made within their environment.

Knowledge of migration patterns, the localisation of specific species at specific times of the year, is vital to the creation and conservation of sustainable fisheries. Due to the seemingly profitable nature of overfishing, it has increasingly become a large threat to the world's oceans and societies that rely on certain fish for their food. WWF (World Wide Fund for Nature) considers overfishing to be one of the world's greatest threats (Morgan, 2020). It is within the interest, both ecologically and commercially, to gain further knowledge of migratory patterns in order to achieve a higher level of sustainability.

Determining reactions to environmental changes in a variety of species, both migratory and native, will allow for the development of offshore structures, which is a leading motivation for the development of fish tracking. Renewable energy sites must be built with ecology in mind, in order to ensure a sustainable environment.

With the rise of both the demand and need for tidal and wind power in the UK and around the world, the majority of these power generators are developed offshore (Hammons, 2011). This includes both offshore wind farms for the development of wind power and for tidal power stations (Manley, 2008). Developments such as these can have huge ecological effects on the wildlife in the area (Manley, 2008). Therefore, it is important to carry out an appropriate study on how the given wildlife would react to such a change in the environment.

Developments in technology have allowed for more in-depth tracking methods to be achieved. Traditionally, catch and release style fishing was used alongside acoustic tags to estimate migration and population statistics. Advancements in new technologies propose a far more detailed set of results. Fish can now be tracked dynamically with a constant flow of location and speed information. Dynamic or active tracking is defined by the real-time knowledge of

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Table 1
Keywords used in the literature search strategy, combining vehicle types with tracking types.

Vehicle Types	"AUV" OR "USV" OR "ASV" OR "Sensor Network" OR "Drone"
	AND
Tracking types	"Dynamic Tracking" OR "Fish Tracking"

the location of the object you are tracking. This is the opposite of passive/static tracking. Passive tracking is unable to locate an object in real-time; instead, the data is stored for later use. Dynamic tracking allows for constant surveillance and therefore mission details can be updated constantly, which is useful for making active decisions.

This paper studies the documented uses of technology to dynamically track the fine-scale movements of different species of fish. By dynamically tracking the fish, theoretically, maps could be drawn using almost exact estimations regarding the whereabouts of fish at a given time. This level of specificity gives a much more detailed view of fish movements and therefore will be far more viable as evidence when studying the reactive behaviour of different species when their environment is modified.

There are several methods of dynamically tracking fish with the use of maritime robotics. These include the implementation of autonomous, semi-autonomous and manual systems. Manual methods require constant human interaction to evaluate information, make decisions based on that information, and then carry out those decisions. In contrast, fully autonomous systems require no human interaction and have Artificial Intelligence that can use real-time data to make intelligent and reactive decisions.

This paper is structured as follows. It reviews the literature regarding dynamic tracking to generate a better understanding of each category using a systematic method called PRISMA (Moher, Liberati, Tetzlaff, Altman and Group, 2009). The PRISMA system was chosen to help provide a methodological approach to a wide-ranging field. PRISMA uses a checklist system to help keep results concise and relevant. The paper then presents why each category was chosen and which is the most efficient and effective at their given tasks. This state of the art review researches the development of this technology in order to provide a better insight into the possible future designs for these systems.

1.1. Study Selection Process

The study selection process is applied according to the PRISMA guidelines (Moher et al., 2009). PRISMA stands for 'Preferred reporting items for systematic reviews and meta-analyses'. It is a thorough process for a systematic review of the search, review and analysis the relevance of studies. The process consists of a four-phase flow diagram, with a 27 item checklist. PRISMA's aim is to improve the reporting of systematic reviews and meta-analysis.

The first step involves a computerised search of key terms and record the number of results from the searching of multiple databases. This is the identification stage of the process. The key terms, seen in Table 1, used for this study involve the vehicles found in fish tracking, in combination with fish tracking itself, along with any form of dynamic tracking.

The next stage is the screening stage. The records are manually screened for duplicates and split into how many records are correct and how many will be excluded from the process. This is important due to the use of multiple database sources.

Once this is complete, the eligibility stage begins. The full-texts are manually accessed for their eligibility and relevance to the study and split into two categories, those that match the criteria and those that are excluded from the study, and the reasons for this. This leaves us with the numbers of studies included in the qualitative synthesis ready for meta-analysis.

The inclusion criteria decided for this study were:

- the article is written in English;
- the article is published in the last 15 years;
- the article concerns a method of tracking;
- the article concerns a marine vehicle or a marine autonomous platform;

- the study includes the method of localizing the tracked target.

The exclusion criteria decided for this study were:

- reviews;
- books;
- conference proceedings.

1.2. Study Selection Results

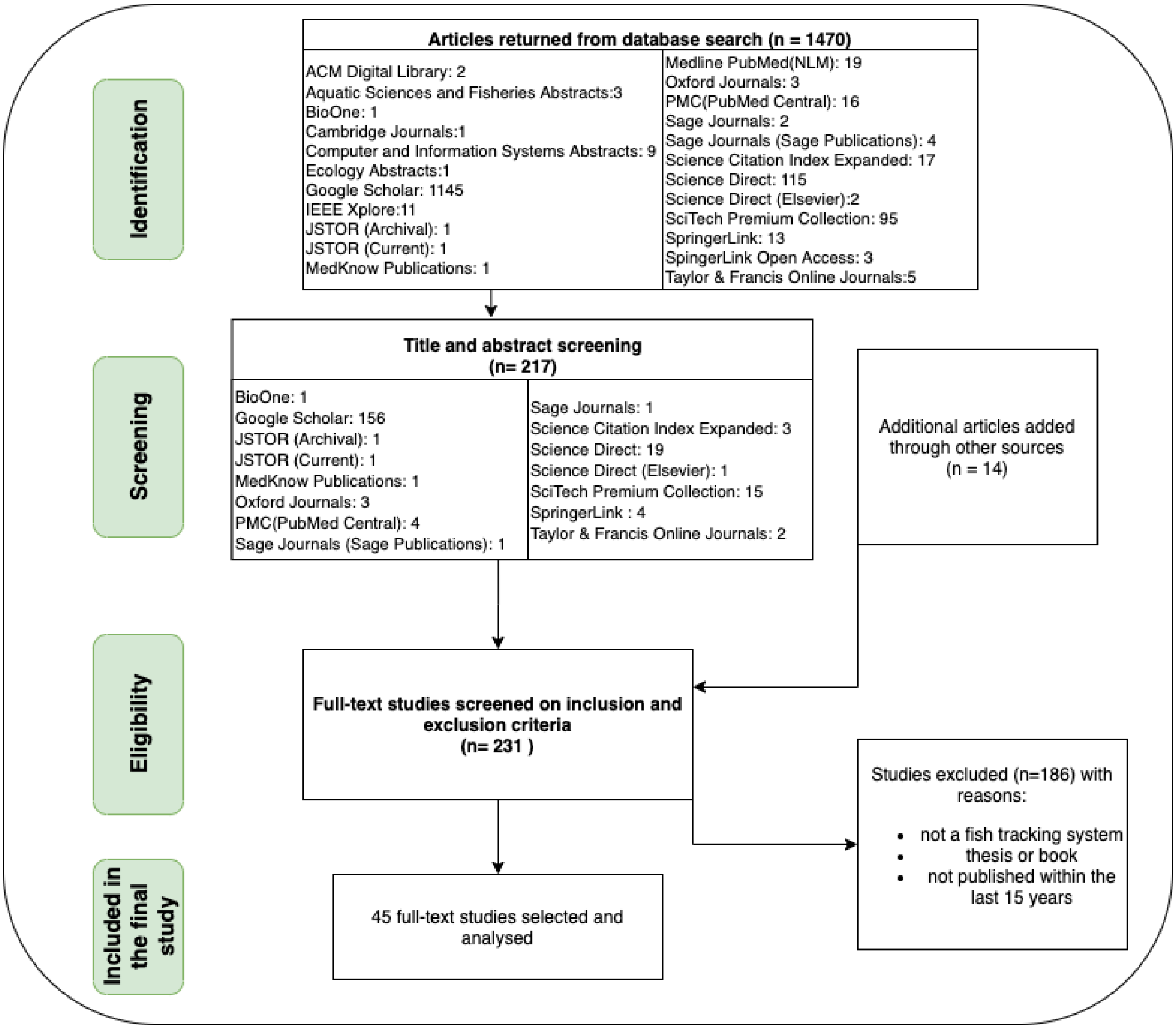

Figure 1: PRISMA flowchart. This shows the results from the literature search.

A simplified breakdown of the results of the PRISMA search can be seen in Figure 1. 1470 articles were initially identified with the search strategies in the 'Identification' process, the specific databases the results were found can also be seen here. These publications were then reduced to 217 during the 'Screening' process. With additional articles found through other sources, 231 publications were then screened for eligibility via full-text studies on the inclusion and exclusion criteria. Finally, 45 papers were selected and analysed for this review after the selection process. This leaves 186 not included, and the reasons for this can be seen in the lower right of Figure 1. See Appendix Table 3 for the full results of the PRISMA search.

1.3. Breakdown of Included Studies Summary

Table 3 and Table 4 in the Appendix shows a summary of the full-text studies, and a simplified analysis of each paper. Table 3 shows the results of the PRISMA search and the specific search terms used for every result. It gives both the total results and then, after the screening process, the relevant results.

Table 4 shows the final full breakdown of the PRISMA search. It displays the meta-data found under each heading. The headings were chosen as the most topics of value to those seeking information into what platforms are used for using robotics to track marine life. Basic information such as reference and date of publishing is included, while more in-depth information is also found. The 'Purpose' column gives information as to the objectives of each study and gives insight into the nature of the paper. What type of vehicle or vehicles used is found under the 'Platform' heading and states if the study uses multiple vehicles. The 'Sensors' and 'Type of System' headings describe their relative information, though depending on the study this information is sometimes not applicable. This could be because the study gravitates more into oceanography investigations as opposed to vehicle design for example. This study includes papers from many areas of research, from Artificial Intelligence to Fish behaviours as long as it meets the criteria, and this can result in the missing information in these headings. Finally the year of publication is also displayed.

2. Platforms

The vehicles most relevant to this study include 'AUVs', 'ASVs', 'Drones' and 'Multi-Vehicle' platforms (the various acronyms used here are defined in each section below). This is because of the autonomous development for robotics platforms. Other platform types have also been included ('ROV's, 'USV's, Manual and 'UUVs') for several reasons. Firstly, so a better understanding of the state of the art of sensory information can be gained, but also because the terms ROV/UUV are often synonymous with AUV. AUVs in a militaristic setting are often referred to as ROVs/UUVs and thus it is important to include these terms on an individual basis if the research is relevant. Figure 2 shows the distribution of the platforms found in the final PRISMA results.

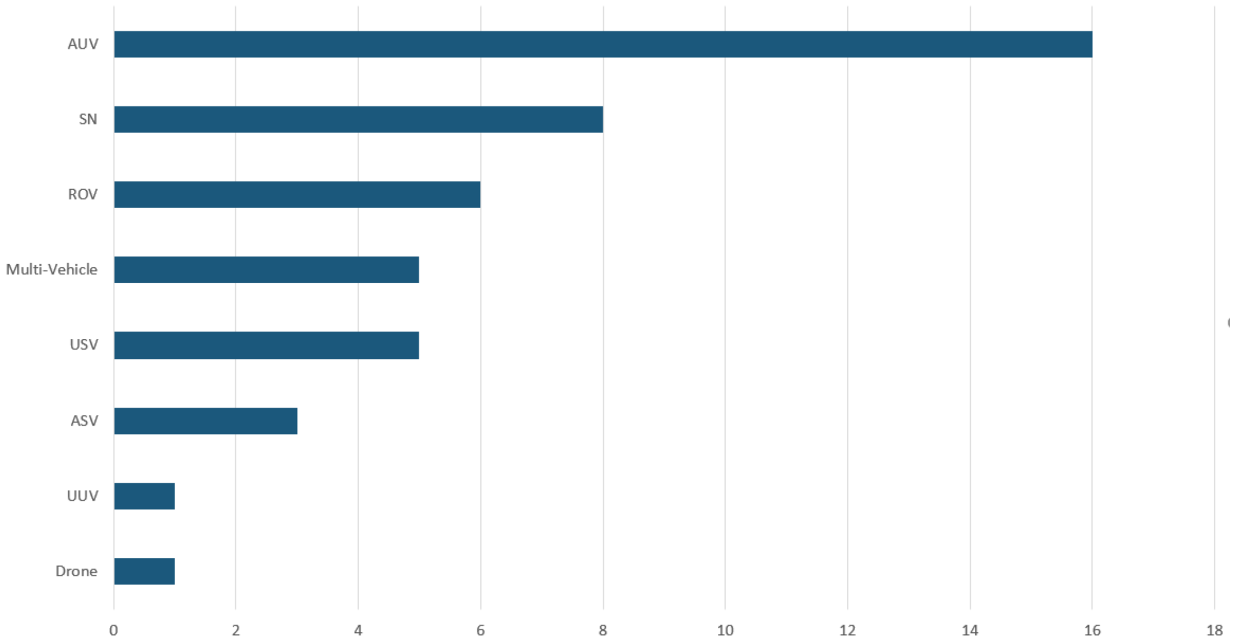

Figure 2: PRISMA bar chart. This shows the quantity of relevant papers for each vehicle type from the literature search.

2.1. Autonomous Underwater Vehicles

The most common platform of choice for developing state of the art autonomous robotics platforms for the use of fish tracking, based on this study, is the Autonomous Underwater Vehicle (AUV). AUVs are an emerging technology that is being used to collect physical, chemical, and biological information in the marine environment (Eiler, Grothues, Dobarro and Masuda, 2013). The vast majority of AUVs discovered in this study implement a torpedo-like design with rear motors for propulsion. However, there are also a few unusual cases such as a study completed by Bi, Niu, Cai, Zhang and Zhang (2014) where the vehicle design is biomimetic, that inherits its features from marine life with, for example, pectoral fins.

As an underwater platform, the system must overcome the physical properties of water in terms of waterproofing, movement and communication. Most also employ a system of GPS, Gyroscopes, Accelerometers, Magnetometer Inertial Measurement Units (IMUs) for help with localization and movement. An accelerometer measures proper acceleration, a gyroscope measures angular velocity, a magnetometer measures magnetic field, and an IMU uses a combination of these three. Systems such as these that are based on the accelerometer or IMU measurements normally consist of several sensor nodes, and can measure kinematic parameters such as orientation, position, velocity, which is particularly difficult in underwater environments. Design of platforms requires an analysis of range, duration, and in the case of underwater vehicles, depth. Battery technologies are constantly evolving, and vehicle power requirements drastically effect these capabilities. Clark, Forney, Manii, Shinzaki, Gage, Farris, Lowe and Moline (2013) found that their AUV platform was able to complete short duration missions, although longer duration missions were difficult. They acknowledged that researchers must address the issue of the limited battery life of AUVs in order to achieve better mission duration, as well as ensuring maximum efficiency by minimizing the sensor configuration profile of the additional sensors added to the platform to reduce drag. The study by Cadena and Ponguillo (2016) shows how design is largely reflective of mission requirements. The technology found in this study has a relatively low range (5km), but as depth is the main concern, has depth capabilities of 600m.

As for communication issues, various studies employ different techniques in an attempt to negate these difficulties. The decision is based on two choices; to attempt to communicate through the water, which comes with its own host of challenges; employ periodic surfacing techniques which require additional autonomous behaviours; or not communicating with the vehicle at all throughout the mission. Studies such as Xydes, Moline, Lowe, Farrugia and Clark (2013) have chosen to communicate through the water. The technique commonly found in these studies to actualise this employs acoustic communications. The vehicle is fitted with acoustic receivers which receive vehicle data from home-base through acoustic pings that are sent at a specified frequency. Another method of communication is through periodic surfacing. Periodic surfacing behaviours are implemented in order to keep communicating with and commanding the vehicle (Pinto, Faria, Fortuna, Martins, Sousa, Queiroz, Py and Rajan, 2013) in an attempt to circumvent the issues found through underwater communication. Far more in-depth communication can be made with the use of GPS, WiFi and Iridium, for example.

There is also the choice to not communicate with the vehicle at all once the vehicle has been deployed. This has the benefit of not having the additional levels of complexity related with periodic surfacing or having additional acoustic communications. However, it does require a large amount of confidence in the autonomous behaviours of the vehicle, as human interaction will not be possible after launch. The study by Lesire, Infantes, Gateau and Barbier (2016), is one such example where the focus is on long-term autonomous missions, with high degrees of autonomy that require no human interaction.

Several systems have been developed using AUVs to track fish, in order to gain an insight into movements and behaviours. Examples include the tracking of Leopard Sharks (*Triakis semifasciata*) (Clark et al., 2013). The study found that the AUV was comparable in efficiency at repeatedly locating the sharks and tracking them with an AUV employing a telemetry based system, when compared to a manually controlled surface system. However, there are some studies such as the work completed by Eiler et al. (2013), where the vehicle was either on par or surpassed the standard vehicle. The surface vehicle was considerably more difficult at detecting tagged fish, especially when there were greater numbers present in the area. The study found that the detection rates and number of tracking successes were significantly greater for the AUV, although this was less definitive in shallow waters (<20 m). This was found for both reference tags, one being a stationary transmitter at known locations and depth, and the other being free-ranging animals located at deeper depths. This study also found the success of the AUV is based on a number of factors which includes the AUV running far more quietly and operating below the thermocline and halocline. However, it also suffers far less noise interference when tracking from the sea surface, as this causes signal degradation. Eiler et al. (2013) also found that an AUV can remove the human bias, as humans tend to focus on areas where they have found a partial track, instead of surveying all areas in an unbiased fashion.

2.2. Sensor Networks

Sensor networks (SN), both wireless and otherwise, are also used as a tool for autonomous tracking and are the second most common platform found in this study. A sensor network consists of spatially distributed sensors, which can be fully autonomous, in order to monitor physical or environmental conditions.

Arrays created using Acoustic Hydrophones can implement passive acoustic systems (Eiler, Evans and Schreck, 2015). These arrays create a specific area within a two-dimensional space that tracks fish movements within the given space. In general, arrays employ a wide variety of implementation techniques, that involve active sonar tracking, GPS tags, and animal-borne telemetry. These systems scale in cost, and can be a cost effective method for small scale deployments, such as in an estuary or river (Tokekar, Bhadauria, Studenski and Isler, 2010). Larger deployments that have a wider tracking areas can have a much larger cost. The addition of implementing a vocalization detection system allow for the tracking of animals that produce ultrasonic clicks. Although dolphins and Harbour porpoises are commonly tracked using vocalization, this method of tracking is extremely specific to these species. Another issue is that the predetermined location for the array is limited in scale and the tracking of migratory fish will be challenging.

Sensor networks can be both static and (in more recent studies) mobile. In the context of fish tracking, fixed sensor networks are deployed to a specific location, such as in the work completed by Xinya al. (Li, Deng, Martinez, Fu, Titzler, Hughes, Weiland, Brown, Trumbo, Ahmann and Renholds, 2015). Using an acoustic telemetry system, they were able to investigate the spatial distribution of migrating juvenile salmon in open-water conditions between two dams. This study was also able to implement 3D tracking up to a horizontal distance of 50m upstream and downstream. Algorithms and prototype vehicles have been developed for tracking longer distances. This can be done using mobile wireless sensor networks (MWSN) with the use of Fish Actuating Devices (FADs). This creates an array that can relocate to gather new data from a different area. An example of this is the study by Brehmer, Sancho, Trygonis, Itano, Dalen, Fuchs, Faraj and Taquet (2019), where FADs, along with both optical and acoustic sensors, were able to monitor fish diversity and abundance in specific ecosystems.

2.3. Unmanned Surface Vehicles

Unmanned Surface Vehicles (USVs) are an emerging technology used to track the fine-scale movements of fish. Generally, USVs are either controlled remotely by humans in real-time or are semi-autonomous (Liu, Zhang, Yu and Yuan, 2016). This is due to challenges such as reliable guidance navigation and control. However, fully autonomous surface vehicles are also being developed that attempt to minimise these issues and rely less on human interaction. These are known as Autonomous Surface Vehicles (ASVs) although some papers still refer to ASVs as USVs when the focus of the paper is more application oriented.

Both USVs and ASVs are a main area of interest for scientific, military and commercial developments for many reasons. Firstly, this type of platform has the advantage of being a low-cost solution (Raber and Schill, 2019). They are much cheaper than other platforms, which makes them more appealing to smaller research teams, or for multiple vehicle missions. They are also far easier to communicate with than their underwater alternatives, which make them even more advantageous in multi-vehicle deployment. Range and power consumption of vehicles is a concern for all vehicle types. However an advantage to using a surface vehicle is access to renewable energy sources. A study by Mousazadeh, Hamid, Elham, Farshid, Ali, Yousef and Ashkan (2017) shows the use of self-propulsion through wind energy and solar panels to power the vehicle-control electronics and sensor payload. They found through testing that the vehicle was capable of long-range (> 5000 km) and long-duration (>500 days).

ASVs also are used to support other autonomous systems. ASVs can be used to track Autonomous Underwater Vehicles (AUVs). Due to the physicality of water, establishing communication to an AUV is difficult. ASVs can be used to support missions and communicate with the vehicle, by tracking the trajectory of an AUV using acoustic signals (Daxiong, Shenzhen, Rong, Ruiwen, Hongyu and Yang, 2013).

Pinto et al. (2013) also used a multi-vehicle setup. This was with the addition of an unmanned aerial vehicle to relay communications back to homebase. An ASV was used in order to establish a connection between a surfacing AUV and relayed information to the aerial vehicle. Their results found that the on-board control and communications infrastructure was flexible. This was in reference to their Wifi and Iridium network systems for communication, and deployment of their control software.

The US Navy initiated its UUV work well before it focused on USVs. However, the recent release of the Navy's USV "Master Plan" indicated that they wished to expand their research in the USV area (O'Rourke, 2020). The reason for this was that the USV's position allows them to relay radio frequency transmissions in air and acoustic transmissions underwater and acts as a middleman between both air and underwater vehicles. Thus they are absolutely essential to a future networked battleground. In recent years, demonstrations have been conducted using USVs to support moving long baseline navigation of UUVs (Curcio, Leonard, Vaganay, Patrikalakis, Bahr, Battle, Schmidt and Grund, 2005). Long baseline is a type of acoustic positioning system used to track underwater vehicles and divers (Milne, 1983). Further evolution of USVs as network nodes in naval applications is likely.

There are also a number of challenges that come with fish tracking using this type of platform. Firstly, sensors such as optical cameras can be greatly affected by the relative instability of a surface vehicle (Liu et al., 2016). These types of sensors are described in many of the studies, but for different reasons. For example, work completed by Steccanella, Bloisi, Castellini and Farinelli (2020), used cameras in an attempt to achieve accurate waterline prediction by studying the reflections, illumination changes, and waves detected by the optical sensors. They also used the cameras for obstacle detection and by extension, obstacle avoidance. Their solution for the instability challenges that derive from surface vehicles was to use a sample of images to base decisions on. Their results showed a high level of accuracy, as opposed to results with single images. There is also a challenge when using acoustic tags and acoustic receivers on the vehicle. The surface of the water can have a refracting effect on the acoustic signal, which can make it difficult to localize the signal (Lv, Zhang, Jin and Liu, 2016).

2.4. Multi-Vehicle Deployment

More recently, many research teams are opting for multi-vehicle deployments over single-vehicle missions. Opting for multiple vehicles focused on a single task has many benefits over using a single platform. These benefits range from increased mission distances, larger tracking capabilities, more accurate tracking information and negate communication difficulties found when communicating through water. Multi-vehicle deployment can mean using multiple different platforms, for example an ASV and a AUV combined to gain the benefits of both, or multiple AUVs in order to increase sensor capabilities or gain more accurate sensory data.

Studies such as Pinto et al. (2013) use both an AUV and an Unmanned Aerial Vehicle (UAV). The researchers tracked Sunfish (*Mola mola*), who are good carriers of sensors, although they travel large distances. The feasibility of such long distance tracks, where the fish position and the areas surrounding the fish are all mapped, was only possible using a multi-vehicle approach. The UAV was tasked with mapping large areas of ocean surface that surrounds the tracked fish, while the AUV was focused on tracking the specific water column. This study also showed how the use of a multi-vehicle deployment can aid in communications, as communication with underwater vehicles is notoriously difficult as mentioned previously. The UAV served as a communications relay between home-base and the multiple vehicles. This technique is found in multiple studies such as the publication by O'Rourke (2020), where the US Navy used ASVs as a communication relay between above surface vehicles or command stations, and AUVs or submarines.

Alternatively, there are other uses to multi-vehicle deployments, for increasing tracking capabilities. More sensors in more locations results in higher level of accuracy when tracking. Therefore developments have been made to create 'swarm' behaviours, where multiple platforms communicate with each other, and collaboratively achieve a common goal. The use of swarm intelligence is an emerging technology with only recent publications according to the PRISMA review. Swarm is a collective-behaviour of a self-organised system. This type of AI can be used with multi-vehicle deployments for more efficient and/or effective missions. The vehicles operate on a network, communicating with each other to achieve a common goal. This is useful for a number of operations, such as surveying large areas. It also has the additional benefit of having a much larger amount of sensors, which is multiplied by the amount of vehicles used. This increase in sensors produces for far more detailed tracking data. Zolich, Johansen, Alfredsen, Kuttenkeuler and Erstorp (2017) provides an example of swarm behaviours used in a fish tracking setting. The design is to use formation control algorithms in order to move the vehicles in synchronization while sharing data on the radio-tagged fish.

Low-cost platforms are often used in combination with swarm intelligence. As multiple vehicles are required, it can be too expensive for research teams to use a large amount of high-cost platforms. Basic USVs are more often selected over more expensive counterparts such as AUVs. In fact, out of four of the review results describing swarm techniques, three of them deployed low-cost USVs. An example of a swarm intelligence platform is the research completed by Lin, Hsiung, Piersall, White, Lowe and Clark (2017). Here, swarm behaviours have been developed for multiple functions. Firstly, the AUVs use a leader/follower multi-platform control system in order to follow collision free paths to the tracked fish. Once the vehicles reach the target, the AUVs initiate a circumnavigation state, where the vehicles loiter around the fish. This, among with other updates to their system such as state estimation upgrades and additional full inertial measurement units, were found to be quite successful. Decreases, such as in mean position estimation error of 25–75% were achieved, tag orientation estimation errors dropped from 80° to 30°, the sensitivity of mean position error with respect to distance to the tag was reduced by a factor of 50, resulting in a significant improvement. Finally, the sensitivity of mean position error with respect to acoustic signal reception frequency to the tag was improved 25 times.

3. Sensors

The sensors embedded on a vehicle are chosen based on the original goal for the vehicle. For example, if the goal is for a vehicle to use optical data and object recognition to track specific fish, optical sensors will be used. This systematic review has discovered that a wide range of sensors have been used, although mention of specific details of these sensors are often neglected in the literature. For example, IMUs and GPS devices are almost universally used in all mobile maritime robotics, as they are required for the most basic operations. Consequently, these devices are often not mentioned, despite them being used. This is also due to them being used by the systems navigation and mission control, and not the focus of the paper. Subsequently they have been excluded from discussion in this section.

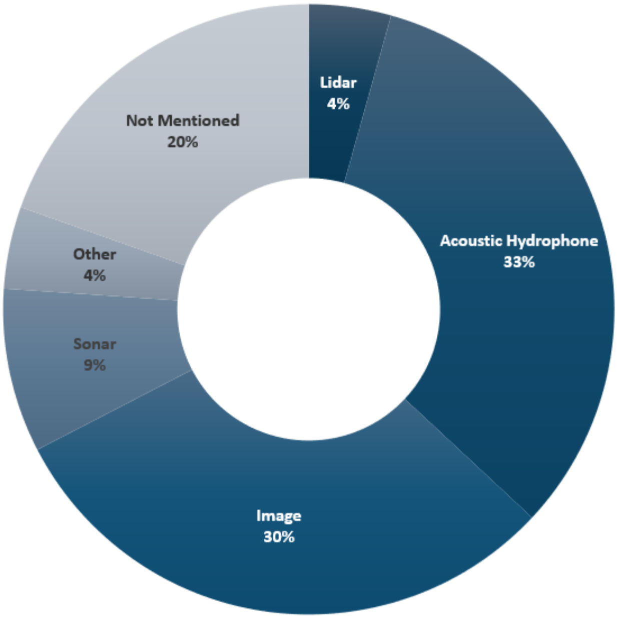

Figure 3: Distribution of sensor types as found in the PRISMA results.

The distribution is relatively similar between the two most commonly used sensors, as seen in Figure 3. With the exception of the aforementioned exclusions, the most commonly used sensors for autonomous marine vehicles are acoustic sensors, with 15 publications and optical sensors with 14 publications. This is interesting as the two different sensors use entirely different methodology for tracking. Nine publications in the PRISMA results shared no details regarding sensors. Sonar was used in four papers in total, equalling 9% of the total results. Both Lidar and 'Other' sensors were used in two papers each. 'Other' sensors refer to selected special cases that are sensors that are extremely specific to the study focus. For example, a paper used chemical sensor for tracking chemical plumes (Marques, Ribeiro, Pinto, Sousa and Martins, 2015). As these are case-specific, they will not be expanded on here.

3.1. Acoustic Hydrophone Sensors

The typical method of tracking fish using hydrophone receivers include tagging individual fish with acoustic transmitters. These acoustic signals are detected and measured by the hydrophone receivers. Often in general fish population and habitat monitoring studies, the use of static location acoustic receivers are used to passively track targets that move through a static array. In recent studies, low-cost in-stream antenna systems for tracking passive integrated transponder (PIT)-tagged fish in small streams are also used. In the case of marine autonomous vehicles, the receivers are often used for more than that. The receivers are still fixed, but to specific locations on the vehicle, as opposed to static locations geographically. Multiple hydrophones are used in the majority of cases in order to gain far more data during a track than the passive arrays. These platforms go beyond simply detecting and monitoring models, but also gain more information regarding 3D positions of the target and increased accuracy of position estimates using time delays between each receiver (Lin, Kastein, Peterson, White, Lowe and Clark, 2014).

Acoustic hydrophones, in the vast majority of cases, are paired in practice with acoustic transmitters. Often referred to as 'tags', acoustic transmitters emit a signal between 30kHz and 200kHz. Together the transmitter and receiver make the acoustic telemetry tracking system. The emitted signal is identifiable and unique, and pings at a fixed or varied interval (Xydes et al., 2013). The requirement of a tag is a drawback of this type of system that is not found in other tracking types. The target of the track must be acquired prior to the mission, in order for the tag to be inserted. This has the flaw that targets cannot be dynamically changed during the mission, and missions often require permits and training to surgically insert the acoustic tags. The size of the target also defines the size of the tag required for the mission, large tags cannot be inserted into small fish. This then has effects on range for the acoustic ping and also the battery life of the transmitter.

The raw acoustic position measurements are then processed by on-board systems in order to provide state-estimation. This can be done using many different types of fish localization algorithms. A few examples of these use linear interpolation that predicts the fish position based on only the last two position movements (Lin et al., 2014). For tracking in a 3-D environment, it is required that at least 4 hydrophones are used for non-linear localisation equations. Particle filters, on the other hand, use a distribution of state estimates to represent the current belief of the target's state (Xydes et al., 2013). The particle filter is designed to first predict the particle state estimate forward in time, and then to correct the model based on new measurements. This is a probabilistic approach and is discussed further in section 4.3. The last example is the behaviour based localization algorithm (Xydes et al., 2013), which is similar to particle filter algorithms. The algorithm first propagates the state of the target, and then updates the data using a Bayes filter to correct the prediction. The approach of Clark et al. (2013) is another example of the use of Particle filters, using state estimators to produce both real-time estimation of a Leopard Shark's (*Triakis semifasciata*) 2D planar poition and velocity, as well as navigational control to follow the tracked target. Their experiments found that the state estimator's error margins were comparable to that of a long-distance manually-tracked system, with the example of a manually controlled boat with boat-based tracking systems.

3.2. Image Sensors

For a vehicle to be a fully versatile and dynamic autonomous system, it must have strong simultaneous localization and mapping (SLAM) computation. The system must have a strong awareness of its immediate surroundings and process this information constantly, in order to avoid any obstacles. LiDAR and Sonar have strong sensory capabilities in this area, however, they can be very expensive and require powerful processing units. Research teams often opt for more low-cost solutions, and this is where optical sensors are appropriate. Recent developments have been made to increase the resolution for these types of sensors, making them far more feasible for this type of research (Raoult, Tosetto, Harvey, Nelson, Reed, Parikh, Chan, Smith and Williamson, 2020). The data from these cameras are processed both in real-time and post-completion of the mission, depending on the mission goal. They are used both in underwater and surface vehicles and have a variety of processing methods.

The choice of optical sensor is highly dependant on both the environment in which the missions are being conducted, and the type of AI used in the design of the system. A review of the software used in these platforms can be found in the Computational & Artificial Intelligence Techniques section below. However, for context in its simplest form, image processing is used to extract information from images and video. This is the reason the environment is important to the type of optical sensor used on the system. For example, one study found in the review opted for ultra low light monochrome cameras, as they were more applicable to low visibility environments (Richards, Smith, Ault, DiNardo, Kobayashi, Domokos, Anderson, Taylor, Misa and Giuseffi, 2016). Cameras such as monochrome cameras can make certain processing tasks easier to implement, for example, object recognition. This study, along with others such as the work completed by Guo, Pan, Shi, Guo, He and Tang (2017), make use of colour restoration and image enhancement algorithms such as Retinex and MSRCR to alleviate issues caused by light scattering and absorption. The studies found that the system was capable of detecting and tracking various targets precisely, with low-power consumption and high real-time performance. The study by Guo et al. (2017) also found that the Video or image cameras also differ to a large extent in practical use. Generally, studies that use video cameras extract the information post-mission using batch processing. This is because video is generally difficult to manage in real-time systems and often takes significantly more processing power to analyse. Image optical sensors, on the other hand, are more often found in real-time systems. This is for many reasons. Images are far easier and less expensive computationally to both take,

Table 2
Discussed software found in PRISMA results and their availability and type of technology.

Name of Technology	Availability	Type of Technology
Computer Vision	N/A	Computer Science Technique
Deep Learning	N/A	Computer Science Technique
Reactive Behaviours	N/A	Computer Science Technique
Swarm Behaviours	N/A	Computer Science Technique
DUNE (Ferreira, Costa, Py, Pinto, Silva, Nimmo-Smith, Johansen, Sousa and Rajan, 2019)	Open Source	C++ Robotics Framework
Ocean Server (Lin et al., 2014)	Proprietary	Mission Navigation Software
Lotek (Clark et al., 2013)	Proprietary	Acoustic Positioning Software
Seebyte Neptune (Haworth, Evans, Mcmanamon and McNally, 2016)	Proprietary	Real-time Sensory Processing
ROS (Quigley, Conley, Gerkey, Faust, Foote, Leibs, Wheeler and Ng, 2009)	Open Source	Robotics Middleware
MOOS-IvP (Benjamin, Schmidt, Newman and Leonard, 2010)	Open Source	Robotics Middleware
MORSE (Echeverria, Lassabe, Degroote and Lemaignan, 2011)	Open Source	Robotics Simulation

store and modify/process. Many of the benefits of video can be reproduced by taking multiple images in succession, but at a user-defined rate, giving more control, while keeping all the benefits of both video and image optical sensors. This helps to trade-off how often information is updated versus how much computation is used.

One of the largest drawbacks of using optical underwater imaging is because these images can contain scatter and noise, especially when capturing "far away" images. This is only exacerbated when light is low, so deep sea exploration is very difficult using these techniques.This is where other technologies such as Sonar or LiDAR is chosen instead.

3.3. Sonar & LiDAR

Another sensor that utilises acoustics for underwater localisation and mapping is Sonar, which uses sound propagation in underwater environments to achieve this. Traditionally sonar types such as ultra-short, short and long baseline sonar are used for localization, mapping and navigation. Though these acoustic positioning systems are found in both Sonar and acoustic hydrophone systems, this review only found reference of these systems in Sonar platforms. Lu, Uemura, Wang, Zhu, Huang and Kim (2018) proposed using a Gabor filter post-scene capture to enhance sonar image contrast. This is combined with the Kalman filter for tracking, a technique also found in the acoustic tracking systems. Real-time tracking systems use algorithms such as that proposed by Lee, Kim, Kim, Myung and Choi (2012) to restore colour images to detect objects. Sonar and LiDAR are similar in their design to map surroundings. Sonar relies on sound to detect objects, whereas LiDAR uses light. The system of using basic filters on LiDAR data has multiple real-world situational problems and can be computationally expensive. For this reason, studies found in this systematic review discovered methods to overcome these issues. Lu et al. (2018) for example developed the system YOLO, which stands for "You Only Look Once" to enhance images and recognize marine organisms to track different species (Lu et al., 2018).

LiDAR was only found to be used in localization, mapping and range finding (Mousazadeh et al., 2017). For this reason, they are rarely mentioned in this paper, as the focus is not on the SLAM capabilities of the vehicle.

4. Computational & Artificial Intelligence Techniques

There is a wide range of computational and Artificial Intelligence techniques used for designing systems for tracking. As mentioned previously, these techniques are very dependant on the sensors the platform uses. The focus of the research influences both the AI techniques and sensors heavily, as each methodology has its own benefits and drawbacks. The PRISMA search resulted in many different approaches to the AI solution. Some publications mention high-level techniques such as deep learning algorithms and computer vision. For example, some publications discuss these far more in-depth and even go further to discuss the systems used to achieve these techniques. Whereas some do not discuss the technologies used in any capacity. For this reason, Table 2. shows the different technologies that are discussed in the research.

4.1. Computer Vision & Deep Learning

Computer vision is a field of Computer Science that deals with gaining knowledge from optical data such as images or videos. This can be used for many different applications and is a broad discipline that many technologies are founded upon. One important Artificial Intelligence technique often used in synergy with computer vision is deep learning.

Deep learning is a subset of machine learning, an Artificial Intelligence technique that optimises performance automatically through experience from previously acquired datasets. Deep learning was inspired by the processing and communication nodes present in biological systems such as the human brain. In a deep learning context, these nodes form an artificial neural network. The word “deep” refers to these networks comprising more multiple layers. From raw input, it uses these multiple layers to extract high-level properties. This can be very effective at image processing, taking raw data input, identifying edges as a low-level layer, and progressing into object recognition in higher-level layers. In terms of maritime robotics, these algorithms can prove extremely effective at object recognition, when combined with data input from sensors such as optical cameras. An example of how effective they can be is provided by Sun, Shi, Liu, Dong, Plant, Wang and Zhou (2018a) where the use of convolutional neural networks have been implemented to extract features from low-contrast, low-resolution underwater videos, a main flaw in image sensors. This research aims to use these techniques to overcome the challenges caused by these low quality videos and also provide a larger training dataset to circumvent future issues with small size underwater training data.

Deep learning refers to a large variety of techniques, including many variations of convolutional neural networks (CNNs) and techniques. Islam, Fulton and Sattar (2019) describes the use of the most commonly used algorthms found in the fish detection field. One of the most commonly used algorithms found by this review is the aforementioned YOLO algorithm, which corresponds to “You Only Look Once". YOLO utilizes a single convolutional network and aims to prioritize speed and recognition, over a more detailed computationally expensive approach. Lu et al. (2018) describes how this type of system can be used for marine robotics. Using a dataset of approximately 1.3 million labelled images and 32 thousand hours of underwater video, a database was created and categorized objects in the data such as shrimp, squid, crab, sharks, sea urchin, manganese, and sand. Several preprocessing layers were applied to the data in order to produce a more easily identifiable image. Many systems of this type use convolutional neural networks in order to detect and identify marine life in imagery, either optical or sonar-based. However, this is not the only type of neural network used on these platforms, and object classification is not the only use of deep learning. Obstacle avoidance is one other application for these techniques in marine robotics.

Another commonly used fish detection algorithm is SSDs or Single Shot Detectors. SSDs is similar to YOLO as it performs object localization and classification in a single pass of the network. This uses the same regression technique as YOLO. When used in conjunction with Mobilenet V2, Islam et al. (2019) found that the additional convolutional layers at the end of the base network provides SSD with an advantage of improved performance over YOLO.

Lin, Wang, Yuan, Yu and Li (2019) used recurrent convolutional neural networks (R-CNNs) to achieve obstacle avoidance. Obstacle avoidance is often a requirement for underwater and surface vehicles, given their autonomous nature and their deployment environments. Recurrent neural networks have proven to give state-of-the-art performance on many tasks of this type including sequence labelling and prediction. In this particular study, with the use of a UUV obstacle avoidance dataset, offline training was used as the learning type for the neural network. R-CNNs were found by Islam et al. (2019) to have much greater detection performances compared to the other methods; however the run-times were often the slowest.

4.2. Reactive Systems

Reactive Artificial Intelligence as its name suggests is purely reactive in its decision-making process (Georgeff and Lansky, 1987). This means it cannot use previous experiences to inform new decisions. This design can be seen as more simplistic and therefore easier to implement than other types of AI involving limited memory, which uses past experiences to influence future choices. Reactive systems are, however, a perfectly viable solution to many autonomy challenges. In terms of marine robotics, a reactive approach can be applied to many of the tasks found in the area. With a large distribution of sensor types on these vehicles, there is a large amount of information being available to react to. One such example of a reactive system is the work published by Tokekar et al. (2010) which used data from radio receivers. Here localization algorithms are used to estimate the position of the craft. The vehicle localises itself within the given environment and reacts to this information to determine how to proceed in its navigational tasks. If the GPS data shows the vehicle is veering off-course, the system can correct itself using this data. From this, the system reacts by creating waypoints to navigate towards.

In tracking, a reactive system can be very effective. This is for several reasons. Firstly, the system is generally far less computationally expensive than limited memory systems. This is beneficial to microcontrollers, that you often find in autonomous marine vehicles, which do not have large amounts of processing power. Reactive systems are also an easy solution to implement in many cases. For example in tracking, if hydrophone data can be processed into a localized target, the vehicle can react to this by navigating towards the acoustic signal, effectively following the tracked target see by Xydes et al. (2013) for example. A system such as this is often easier to implement than using large (already acquired) datasets to train machine learning models.

4.3. Probabilistic Approach to Tracking

Many platforms found in this study use Bayesian inference (a probabilistic approach) to solve a wide variety of issues found when developing marine robots. One of these issues, a main component of acoustically tracking targets is localisation. Research completed by Xydes et al. (2013) aims to improve localisation accuracy and temporal resolution for tracking acoustically tagged fish using a probabilistic approach. The results showed that when compared with interpolating raw acoustic positioning methods, their method of using a Bayes Filter and a Particle Filter showed a decrease in error in location predictions.

Filters such as the Bayes Filter are not only used for localising tracked targets, but also self-localisation. Simultaneous localisation and mapping (SLAM) is a commonly used method in robotics for navigation and mapping. SLAM refers to the mapping of an unknown environment, and simultaneously localising an agent within that environment. Probabilistic approaches such as particle filters, extended Kalman filters and Covariance intersection are common in SLAM techniques. An example of this can be found in the work done by Blanco, González and Fernández-Madrigal (2008), which compares the use of non-probabilistic batch optimisations against modern probabilistic techniques. The process employs Bayesian estimation which is based on the Rao-Blackwellized Particle Filter and an extended Kalman Filter. The work concluded that the Bayesian solution was a more desirable solution than batch processing, reasoning that the consistently updated information from new observations was a desirable trait.

4.4. Proprietary Systems

Another category of systems found in the PRISMA results is proprietary software, such as SeeByte's Neptune or Lotek's positioning systems. These vary from fully deployable vehicles with preinstalled software for running waypoint missions, hydro-acoustic positioning systems that are sold in combination with state-estimation systems, or a combination of the two, with reactive Artificial Intelligence such as Neptune.

4.5. Open-Source Solutions

The final type of systems are those that are built using open-source middleware solutions, often open-source robotics middleware frameworks. These frameworks such as ROS (Quigley et al., 2009) and MOOS-IvP (Benjamin et al., 2010) are essentially a collection of libraries which help design and implement robotics platforms. Open source means the libraries are often developed in a collaborative manner, and therefore can be quite large in size and applicable to a variety of applications. These tools allow users to build their own systems independently, and therefore are sometimes neglected in the literature. The frameworks themselves vary in scope. Some like Robotics Operating System (ROS), for example, aim to provide libraries to any type of Robotics platform, whereas MOOS-IvP is specifically designed with marine autonomy in mind.

5. Challenges & Future developments

This paper performed a systematic state-of-the-art review of publications concerning autonomous maritime tracking systems over the last 15 years. There is a clear emergence in the field with regards to multi-vehicle deployments. Papers that use this method of deployment are only found in recent publications within the past four years. The low-cost accessibility of multiple simplistic USVs and more detailed sensory results is ideal for small research teams. This is countered by the increased cost and greater complexity of deploying multiple vehicles, for which there is, as of now, a smaller amount of research. Another reason for this could be that swarm-based autonomy is more difficult to achieve than waypoint or reactive based systems. As more developments in this area make the technology more available, we would expect research to continue and become a more prominent topic, especially in fish tracking and environment surveying.

In addition to this, the use of multiple vehicle deployments with multiple vehicle types is also an area of growing interest. As stated by the US Navy, this provides communication infrastructure where previously communication was difficult to achieve. Using a network of underwater and surface vehicles that are able to communicate, you can also include other vehicles types such as Unmanned Aerial Vehicles to support missions that require aerial data.

As the price of LiDAR reduces over time, we would expect a further increase in the use of LiDAR systems over optical sensor systems. Price is currently the main advantage of optical sensors in this setting, as visual prompts are not required as they are with other autonomous vehicles such as driverless cars. With LiDAR giving far quicker and more accurate 3D results, it seems evident that the trend of LiDAR being favoured will continue.

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A. Appendix

Table 3: Results of the search and the database where those results were located.

Database	Search Term	Result	Relevant
ACM Digital Library	“Sensor Network” “Dynamic Tracking”	2	0
Aquatic Sciences and Fisheries Abstracts	“AUV” “Fish Tracking”	3	0
BioOne	“Drone” “Fish Tracking”	1	1
Cambridge Journals	“AUV” “Dynamic Tracking”	1	0
Computer and Information Systems Abstracts	“AUV” “Fish Tracking”	9	0
Ecology Abstracts	“AUV” “Fish Tracking”	1	0
Google Scholar	“AUV” “Dynamic Tracking”	116	11
Google Scholar	“AUV” “Fish Tracking”	176	65
Google Scholar	“Drone” “Dynamic Tracking”	130	8
Google Scholar	“Drone” “Fish Tracking”	47	4
Google Scholar	“Sensor Network” “Dynamic Tracking”	517	14
Google Scholar	“Sensor Network” “Fish Tracking”	69	16
Google Scholar	“USV” “Dynamic Tracking”	16	3
Google Scholar	“USV” “Fish Tracking”	29	16
IEEE Xplore	“ASV” “Fish Tracking”	2	0
IEEE Xplore	“Drone” “Dynamic Tracking”	2	0
IEEE Xplore	“Sensor Network” “Dynamic Tracking”	3	0
IEEE Xplore	“Sensor Network” “Fish Tracking”	1	0
IEEE Xplore	“USV” “Fish Tracking”	2	0
JSTOR (Archival Journals)	“Drone” “Fish Tracking”	1	1
JSTOR Current Journals	“Drone” “Fish Tracking”	1	1
MedKnow Publications	“Sensor Network” “Dynamic Tracking”	1	1
MEDLINE/PubMed (NLM)	“Sensor Network” “Dynamic Tracking”	5	0
MEDLINE/PubMed (NLM)	“Sensor Network” “Fish Tracking”	3	3
MEDLINE/PubMed (NLM)	“Drone” “Dynamic Tracking”	3	0
MEDLINE/PubMed (NLM)	“Drone” “Fish Tracking”	1	1
MEDLINE/PubMed (NLM)	“USV” “Fish Tracking”	1	0
MEDLINE/PubMed(NLM)	“AUV” “Dynamic Tracking”	3	0
MEDLINE/PubMed(NLM)	“AUV” “Fish Tracking”	2	0
Oxford Journals	“AUV” “Fish Tracking”	1	1
Oxford Journals	“Sensor Network” “Fish Tracking”	1	1
Oxford Journals	“Drone” “Fish Tracking”	1	1
PMC (PubMed Central)	“AUV” “Dynamic Tracking”	2	0
PMC (PubMed Central)	“AUV” “Fish Tracking”	1	0
PMC (PubMed Central)	“Drone” “Dynamic Tracking”	3	0
PMC (PubMed Central)	“Drone” “Fish Tracking”	1	1

Table 3 continued from previous page

PMC (PubMed Central)	“USV” “Fish Tracking”	1	0
PMC (PubMed Central)	“Sensor Network” “Dynamic Tracking”	5	0
PMC (PubMed Central)	“Sensor Network” “Fish Tracking”	3	3
Sage Journals (Sage Publications)	“Dynamic Tracking”	1	1
Sage Journals	“AUV” “Dynamic Tracking”	1	0
Sage Journals	“AUV” “Fish Tracking”	1	1
Sage Journals (Sage Publications)	“Drone” “Dynamic Tracking”	1	0
Sage Journals Sage Publications	“Sensor Network” “Dynamic Tracking”	2	0
Science Citation Index Expanded	“AUV” “Fish Tracking”	17	3
Science Direct	“Dynamic Tracking”	3	1
Science Direct	“Fish Tracking”	5	3
Science Direct	“AUV” “Dynamic Tracking”	9	3
Science Direct	“AUV” “Fish Tracking”	19	6
Science Direct	“Drone” “Fish Tracking”	3	1
Science Direct	“Sensor Network” “Dynamic Tracking”	62	3
Science Direct	“Sensor Network” “Fish Tracking”	4	2
Science Direct (Elsevier)	“AUV” “Fish Tracking”	1	1
Science Direct (Elsevier)	“Drone” “Fish Tracking”	1	0
SciTech Premium Collection	“Dynamic Tracking”	1	0
SciTech Premium Collection	“ASV” “Fish Tracking”	4	1
SciTech Premium Collection	“AUV” “Dynamic Tracking”	12	0
SciTech Premium Collection	“AUV” “Fish Tracking”	14	4
SciTech Premium Collection	“Drone” “Dynamic Tracking”	6	0
SciTech Premium Collection	“Drone” “Fish Tracking”	2	1
SciTech Premium Collection	“Sensor Network” “Dynamic Tracking”	46	4
SciTech Premium Collection	“Sensor Network” “Fish Tracking”	5	5
SciTech Premium Collection	“USV” “Fish Tracking”	3	0
SpringerLink	“Dynamic Tracking”	1	1
SpringerLink	“ASV” “Fish Tracking”	1	1
SpringerLink	“AUV” “Dynamic Tracking”	3	0
SpringerLink	“AUV” “Fish Tracking”	3	0
SpringerLink	“Drone” “Dynamic Tracking”	1	0
SpringerLink	“Sensor Network” “Dynamic Tracking”	3	1
SpringerLink	“USV” “Fish Tracking”	1	1
SpringerLink Open Access	“AUV” “Fish Tracking”	1	0
SpringerLink Open Acess	“Sensor Network” “Dynamic Tracking”	2	0
Taylor & Fancis	“Sensor Network” “Dynamic Tracking”	3	1
Taylor & Francis	“AUV” “Dynamic Tracking”	2	1

Table 4
The final results of the PRISMA search. This figure shows the purpose of each publication, and what vehicle types, system types and sensors each paper mentions.

Ref.	Platform	Purpose	Sensor	Type of System	Year
(Mousazadeh et al., 2017)	ASV	Autonomous, Navigation; Hydrography; Surface vehicle; Monitoring	Lidar, Radar, GPS, IMU, stereo sensors	Multi-control, autonomy, independant	2017
(Plonski, Hook, Peng, Noori and Isler, 2016)	ASV	Sonar; robot sensing systems; collision avoidance; sonar navigation; robot sensing system; habitat monitoring; obstacle avoidance	Sonar	N/A	2016
(Steccanella et al., 2020)	ASV	Water detection; Autonomous surface vessels; Robotic boats; Robot vision; Water quality monitoring	N/A	Computer Vision	2020
(Lin et al., 2014)	AUV	Autonomous underwater vehicles; motion control; multi-robot systems; position control; State estimation	Directional hydrophone	Lotek; Oceanserver; State Estimation; Swam	2014
(Cong, Fan, Hou, Fan, Liu and Luo, 2019)	AUV	Underwater; Underwater robot; Visual summarization; Visual saliency; Visual tracking; Robot vision; Video analysis;	Led lights, 8 cameras, imaging sonar, side sweep sonar, 7 collision sonar, depth sonar, ultrashort/long baseline sonars	Computer Vision	2019
(Clark et al., 2013)	AUV	AUV tracking and following shark; Acoustic telemetry	Acoustic Hydrophones	OceanServer; Lotek; State Estimation	2013
(Xydes et al., 2013)	AUV	Fish tracking; Acoustic tagging; State estimation; Particle filtering; Bayesian filtering	Acoustic tagging	Independant	2013
(Sun et al., 2018a)	AUV	Deep learning; Transfer learning; Computer Vision; Object detection; Underwater video analysis	Cameras	Deep learning	2018
(Asif and Arshad, 2006)	AUV	Underwater target tracking; Kalman Filter; Active contour; Offshore structures	CCD Camera	Computer Vision; Feature extraction; State estimation	2006
(Hung, Liu, Tsai and Lin, 2008)	AUV	Bionic robotic fish for fish tracking	CMUcam2 vision sensor and RF module	UART serial transmission	2008
(Bi et al., 2014)	AUV	Biomimetric Underwater Vehicle; Waypoint tracking	Heading sensor	N/A	2014
(Kumar, Painumgal, Kumar and Rajesh, 2018)	AUV	Vision based tracking of marine animals; photo mapping of seafloor	IMU	Computer Vision; Image Tracking Processing	2018
(Horimoto, Toshihiro, Kofuji and Ishihara, 2018)	AUV	Wild-animal tracking by an AUV without attaching any tag to them,	Multi-beam imaging sonar	deep learning	2018
(Smith, Hsiung, White, Lowe and Clark, 2016)	AUV	Marine mammal tracking; Stochastic processes; Control systems; Feedback control	N/A	Swarm	2016
(Cao, Sun and Jan, 2018)	AUV	Multi-AUV; Cooperative Target Search; Dynamic and Static targets	N/A	Particle Swarm Optimization Algoirthm	2017
(Cadena and Ponguillo, 2016)	AUV	Autonomous Underwater Vehicle; FPGA; Inertial Navigation System; Computer Vision	Optical Dissolved Oxygen sensor	Computer Vision	2016
(Cong et al., 2019)	AUV	Novel event analysis for human-machine collaborative underwater exploration	PanCtiltCzoom (PTZ) camera and static cameras	N/A	2019
(Lu et al., 2018)	AUV	Deep-sea Organism tracking; Deep Learning	Sonar	Deep learning; Kalman filter	2018
(Richards et al., 2016)	AUV	Bottomfish fishery-independent survey	Ultra Low light sensor	stereo-photogrammetric software	2016

Table 4 continued from previous page

Ref.	Platform	Purpose	Sensor	Type of System	Year
(Lowerre-Barbieri, Kays, Thorson, Wikelski and Browman, 2019)	Drone	Identify fisheries management data; addressing challenges with use of drone and sensor networks	Acoustic	N/A	2019
(Lin et al., 2017)	Multi-Vehicle	Multi-AUV tracking; Acoustic telemetry; Shark Tracking	Acoustic Hydrophones	Lotek	2017
(Pinto, Dias, Pereira, Caldas, Rodrigues, Sousa, Py and Rajan, 2015)	Multi-Vehicle	Long distance fish tracking; Multi-vehicle deployments;	Acoustic sensors; GPS; Video Camera	IMC Communication Protocol; Iridium; DUNE for AUVs and UAVs	2015
(Ferreira et al., 2019)	Multi-Vehicle	To observe dynamic oceanographic phenomenal	Acoustics; WiFi; Iridium	DUNE	2019
(Lesire et al., 2016)	Multi-Vehicle	Multi-robot cooperation; Autonomous vehicle; Software architecture	Camera, lasers, GPS, inertial measurement unit	MORSE	2016
(Marques et al., 2015)	Multi-Vehicle	Cooperative Control; Swam; Tracking chemical plumes	Chemical Sensors	IMC, NVA, DUNE	2015
(Raoult et al., 2020)	ROV	Fish community sampling; Underwater surveying; Replacing human snorkelling	Cameras	N/A	2020
(Yim, Clark, Peters, Prodanov and Fidopiastis, 2013)	ROV	ROV-based tracking of a shallow water nocturnal squid	Monocular vision system	Image processing	2013
(Dunlop, Benoit-Bird, Waluk and Henthorn, 2019)	ROV	Provide new data on difficult to study marine life;	Multibeam Echosounder	Pure acoustic data processing	2019
(Nian, He, Yu, Bao and Wang, 2013)	ROV	Fish Ethology; ROV, Underwater Vision System; Image Enhancement; Curve Evolution; Particle Filtering	Optical Sensor	Image Processing; Image enhancement	2013
(Guo et al., 2017)	ROV	Spherical amphibious robot; Gaussian mixture model; moving target detection; system-on-chip (SoC); visual tracking	Optical sensors, Lidar, laser-line scanning, photometric stereo	Image processing, SoC	2017
(Zhou and Clark, 2006)	ROV	ROV; Underwater tracking; computer vision with cameras; image processing; image sementation; feature extraction	Single optical camera	Image processing; feature extraction	2006
(Sun, Yuan, Li, Xu and Guan, 2018b)	SN	Target tracking; heuristic algorithms; energy consumption; adaptive sampling; dynamic uncertainty threshold adjustment	Acoustic Sensors	Adaptive Sampling Algorithm	2018
(Li et al., 2015)	SN	Acoustic telemetry; 3D tracking; JSATS-cabled reciever system	Acoustic Telemetry System	N/A	2015
(Brehmer et al., 2019)	SN	Monitoring Fish Communities around Drifting FADs	Fish aggregating device; multibeam echosounder	multibeam echosounder software; image processing	2019
(Eiler et al., 2015)	SN	Tracking Chinook Salmon; Sensor Networks; Payload control; Acoustic Telemetry	Hydrophones	N/A	2019
(García-Magariño, Lacuesta and Lloret, 2017)	SN	Aquaculture; Simulators; Oceans; Sensors; Fish;	Multibeam Echosounder, Hydrophones	agent-based simulator	2017
(Luo, Han and Fan, 2018)	SN	Review; underwater target tracking; instrument-assisted method; mode-based method; tracking optimization method; review	N/A	N/A	2018
(Aamer and Ebrahim, 2013)	SN	wireless sensor networks; target tracking; energy consumption; reporting frequency	N/A	N/A	2013
(Tokekar et al., 2010)	SN	Robotic Sensor Networks; Omintor common carp tagged with radio tramsmitters; robotic craft	Radio recievers	Reactive, localization techniques	2010
(Zolich et al., 2017)	USV	Unmanned vehicles; hydro acoustic fish-tag position estimation; Unmanned Surface Vehicles; mobile array, swarm behaviour	Acoustic receivers	Swarm	2017
(Haworth et al., 2016)	USV	Vehicles; Ocean temperature; Servers; Sea surface; Adaptive systems	Multibeam Echosounder, Iridium, Wifi, Radio, Email, Acoustic comms	Neptune - SeeByte	2016
(Sousa, Luís, Sargento and Pereira, 2018)	USV	Aquatic mobile sensing platform, delay tolerant network, forwarding strategies, link quality estimator, low-cost systems, simulation and real experimentation, unmanned surface vessels	N/A	Swarm, Delay-Tolerant Network	2018
(Liu et al., 2016)	USV	Literature review of recent progress in USVs development	N/A	N/A	2016
(Demetillo and Taboada, 2019)	USV	Real-Time Water Quality Monitoring	Water quality sensor	Independant	2019
(Lin et al., 2019)	UUV	Online obstacle avoidance planning method; unmanned underwater vehicle; clockwork recurrent neural network	N/A	Recurrent neural network, Simulation	2019

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