Autonomous Underwater Robotic Electric Vehicles for Inter-Robot Line-of-Sight Tracking and Range Communication

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***Abstract*— The use of underwater robotic vehicles (URVs) for scientific inspection of the deep sea, oceanographic mapping, littoral survey, exploitation of underwater resources, protection of the marine environment, and so on, has grown dramatically in recent years. An underwater robot is more difficult to design than a vehicle for use on land or in space. In order to circumvent this issue, we offer a hybrid optimization approach for AUV path planning in an obstacle-filled environment subject to communication limitations. To coordinate several AUVs in a fixed topology environment, a PD controller is employed. A remotely operated underwater vehicle (ROV) is a type of submersible underwater vehicle that can operate without human intervention. It is controlled by an on board computer to perform assigned tasks. Due to the intricacy of the AUV motion control problem, a simulation environment was built in MATLAB/SIMULINK utilising the specifications of the widely used INFANTE AUV. The simulation studies have analysed the control performances under a variety of motion control scenarios, including coordination control, path tracking, and obstacle avoidance.**

Keywords—AUV, Inter robot of sight, Tracking range communication.

I. INTRODUCTION

There are several applications for autonomous robots, including the surveying and exploration of hazardous environments. In underwater situations, such as oil rigs, dams, and shipyards, even the most seasoned divers are not completely safe. The ability to withstand damage from both internal and external sources is essential for vehicles to function in these hostile settings. When problems aren't identified and fixed, the car acts up or gets stolen for no apparent reason [1]. The ability of a vehicle to coordinate with others on the road can be hampered by factors outside of its control, especially if communication breaks down. There has been a lot of effort put into developing fault-tolerant systems, but this challenge only grows as system complexity and operational environment diversity evolve. Performing the ever-increasingly complicated duties expected of robotic vehicles necessitates similarly intricate networks of parts. These networks are prone to errors that pose threats to the robot and its environment [2]. Self-driving cars need a system to deal with malfunctions in their interconnected parts. Model-based fault diagnosis (MBFD) is a typical approach to this issue; it includes comparing the observed behaviour of a system with a model that specifies the system's nominal and problematic behaviour in order to determine where the fault lies. Given the efficiency with which MBFD's model verification procedure can be carried out, it is generally preferred to knowledge- or data-driven diagnosis approaches [3]. However, given the nominal input to the system, MBFD expects all errors to generate distinct behaviours. A system is said to be partially observable if this is not the case; in such a case, many errors can lead to the same observable behaviour.

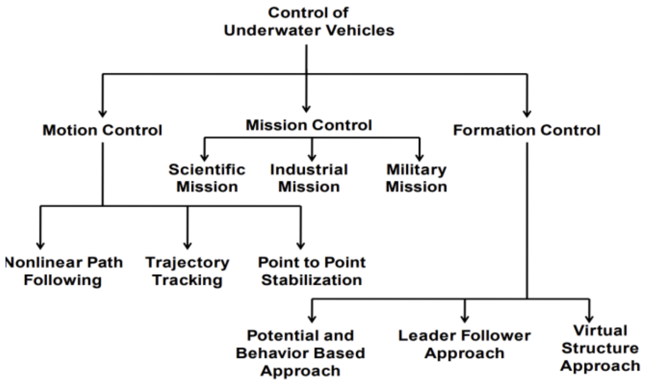

Fig 1: types of underwater Vehicles

Since AUVs are used extensively in fields as diverse as marine security and warfare, oceanography, and the inspection and maintenance of submerged structures, these machines have garnered a lot of attention [4]. During most tasks, rapid mobility and a high degree of dynamic responsiveness are necessities. Notable challenges in building AUV control systems make this a very difficult subject, nevertheless. Controlling AUVs is challenging because of their highly nonlinear, time-varying dynamic behaviour, uncertainties in the hydrodynamic coefficients, high-order dynamic model with robotic manipulator, ocean disturbances, and changes in the centres of gravity and buoyancy of the system caused by the motion of the AUV manipulator [5-8]. Moreover, due to the dynamic shifts in the marine environment, online tuning of an AUV's controller gains is a challenging operation. Consequently, it is preferable to have a control module with self-tuning capability, intelligence, and robustness against uncertain unstructured environments with multilateral control challenges. As can be seen in Fig. 1, the term "control" is used to describe a wide variety of research projects in the existing literature on the topic of underwater vehicle control. We believe that these investigations can be broken down into three distinct subfields: motion, mission, and formation control.

II. BACKGROUND

For precise manoeuvring control of an AUV, it is necessary to create a highly sophisticated and difficult adaptive control law. Furthermore, because of unfavourable oceanic conditions, nonholonomic constraints, highly nonlinear, time-varying, and their model has strong coupling among the motions of six degrees of freedom (6-DOF). Hydrodynamic coefficient fluctuations, unreliable operating conditions, and random disturbances like ocean waves, tides, and currents can have a significant impact on the longitudinal and lateral motions of underactuated AUVs [9]. Exploration of ocean resources, assessment of the environment, and protection of the ocean environment from pollution are just a few of the many marine research applications that have given AUVs a high profile. These missions necessitate high accuracy route tracking along a predetermined course, as well as excellent manoeuvrability. This motion is an attempt to subvert the norm of adding more restrictions on AUVs' motion behaviour during manoeuvring. Point stabilisation, way point tracking, formation control, nonlinear route following, and trajectory tracking are only some of the activities that benefit from precise steering and diving control of an underwater vehicle [10-13]. Because of this, the control law is formulated in a way that makes it possible for the AUV to converge on and follow the route of interest in space without being constrained by any particular time constraints. The AUV's navigation either maintains a steady course or adjusts course based on deviations from a predetermined reference point. Because autopilots can be programmed for planar motion, navigation is more stable and risk-free.

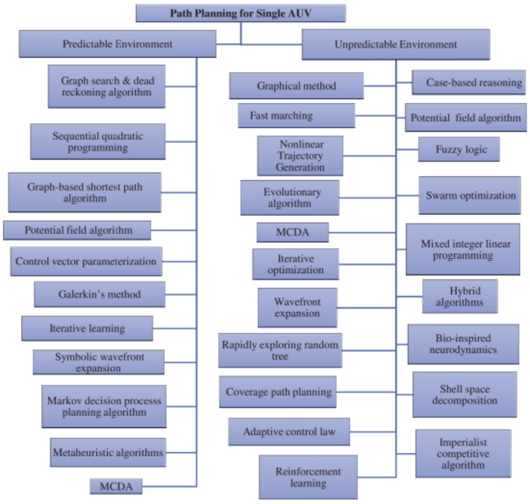

Fig 2: Path planning of single AUV

Due to the limited bandwidth of undersea communication channels, effective communication in an underwater environment is challenging [14-15]. Therefore, AUV route planning is difficult work. Here, we make an effort to classify the literature on AUV path planning, taking into account both deterministic and stochastic marine environments. In Figure2, we have a visual representation of the several optimization strategies that may be found in the literature to build optimal pathways for a single AUV. Oceanic conditions are susceptible to change. However, for many uses, the impact of the marine environment on the path planning may be estimated and deemed predictable. For an AUV operating in a known environment, path planning involves finding the safest way to get from its starting point to its final destination, taking into account any impediments it may encounter along the way.

III. METHODOLOGY

Large sensor, computer, and communication networks are the norm in robotic systems. The successful communication between exterior devices often requires the participation of interior devices that must pass on data. Fig 3 displays one such network. In order for the surface laptop to get information from the Inertial Measurement Unit (IMU), current monitor, or Doppler Velocity Logger (DVL), the information must first travel through a few intermediate devices. Any one of these intermediate devices failing can result in a communication breakdown that appears to originate from the same source. Such conditions give rise to partially observable systems and may result in scenarios where the system is undiagnosable34 and additional data is required for a diagnosis. 35 If there is a breakdown in communication between two gadgets, the only parts of the system that need to be checked out for diagnosis are those that sit between the two gadgets. Since the communication topologies of most autonomous vehicles are loop-free, this can be accomplished by analysing a network of devices of the type depicted in fig. 4. Three serial cables and two intermediate computers are used to transmit data from computer 1 to computer 4. Those two devices could be any two in the AUV communication network that aren't talking to one another.

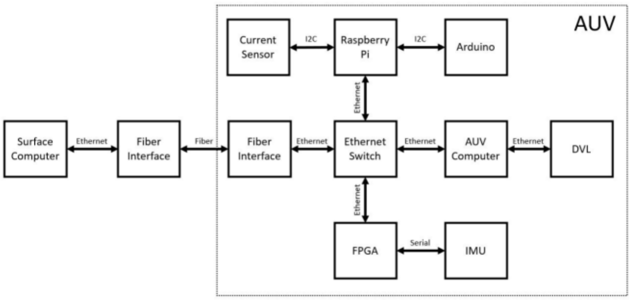

Fig 3: Block diagram for attonamous underwater vehicle

Its ability to withstand parameter uncertainty and perturbations has made SMC a popular tool in nonlinear control for trajectory tracking. In this case, SMC uses a virtual delay and/or Dropout strategy to update the leader's states. As can be seen in Figure 5, it reflect the value of tracking via SMC with Packet Delay and/or Dropout (SMC-PD).

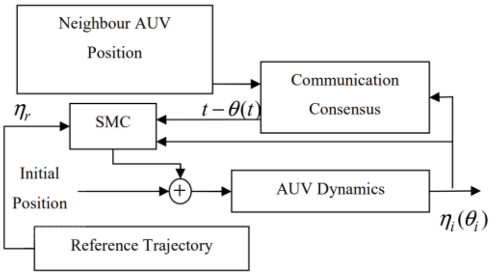

Fig 4: Proposed formation Controller

If you accidentally change an unknown parameter, the SMO won't notice. In the event of an error at the output, it would enter the system in place of the incorrect signal. Using the switching function, the system of interest may exhibit the desired behaviour.

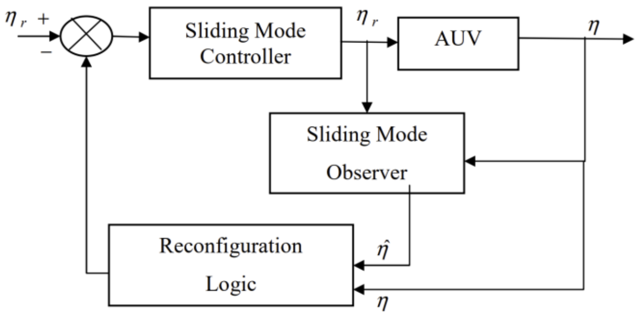

Fig 5: Slidemode controller fomation

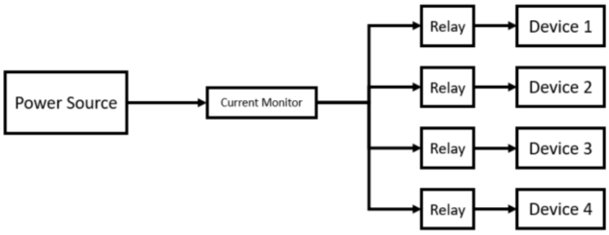

Fig 6: example of EV Monitor

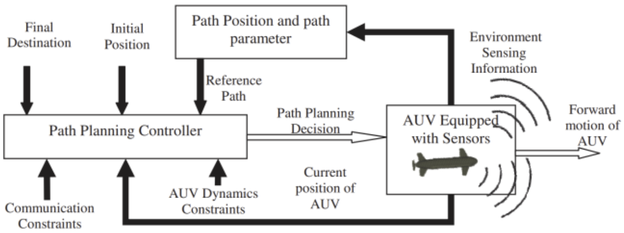

Fig 7a: Path panning Organizer

IV. Results

It was determined that the salinity of this body of water was 0.1 parts per thousand and the temperature was 32.2222 degrees Celsius on the day of testing. (sea water has a salinity of 35 ppt and brackish water has a salinity of 0.1 ppt or less.) Ambient noise was measured and found to be below the modems' internal noise level of 81dB. In Fig 7b, we can see a comparison between the measured SNR during modem testing at Jordanelle and the SNR we obtained using the aforementioned formulae. Up to 1000m, the predicted SNR closely tracks the measured SNR, as shown in the figure. The maximum range of the Seatrac modems is also 1000m, so this should be more than enough to cover all of the simulated environments we use. It is now possible to determine the likelihood of receiving a packet from one agent to another by using the SNR determined above. The method for doing this varies depending on the modem.

In Fig 8, we see a scatter plot of the packet loss probability versus the measured SNR in Jordanelle. The Jordanelle data's measured packet error rate (PER), calculated by dividing the actual number of packets received by their intended number, has also been shown. One should keep in mind that this information is not designed to serve as proof that the probability model is correct.

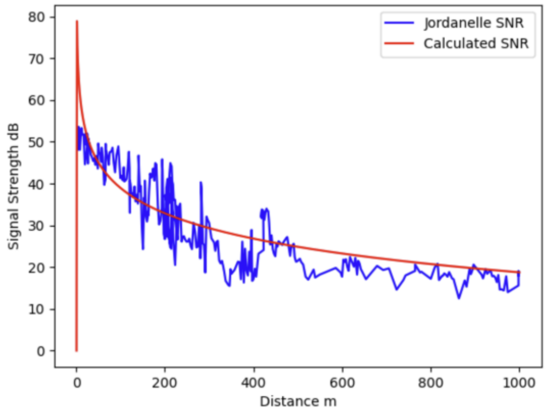

Fig 7b: Signal strength of SNR ratio

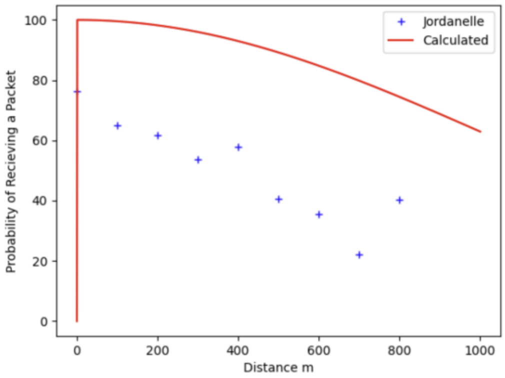

Fig 8: Probability of receving packets

Three AUVs act as followers, as shown in Figure 9, and create a formation in shallow water by following the virtual leader along the path it chooses using SMC-UKO. The shallow water has a greater impact on AUV 3, the follower, thus its trajectory does not effectively match that of the leader AUV.

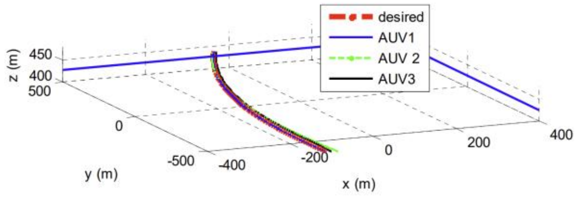

Fig 9: UAV formalation using trojectory

Since the reference path is continuous and differentiated, most studies concentrate on this particular control problem for tracking a moving target. In particular, the oscillations in the path following response are brought on by the initial state error value. As a first step, we analysed how to follow a straight line, and we came up with the following equations for the ideal positions of the AUV in the horizontal plane: xd = 0.02 t + 2 and yd = 0.05 t 1. Fig. 10 displays the simulation outcome of straight line tracking. It only takes 2.7 seconds for DFSMC and 2.9 seconds for EDFSMC to catch up and land the AUV on the required path smoothly, but FSMC and SMC need 3 seconds and 3.5 seconds, respectively, to do the same.

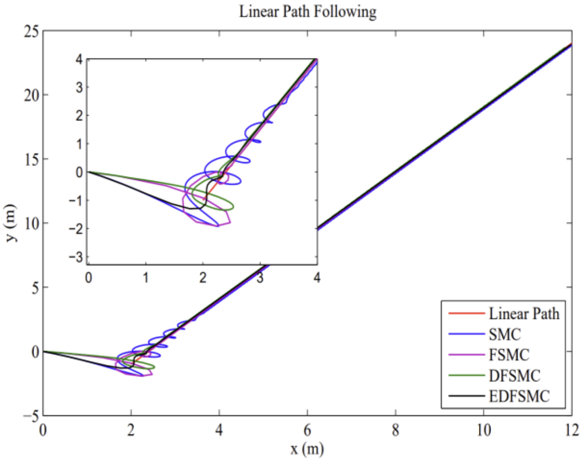

Fig 10: Linear path tracking response in UAV

V. CONCLUSION

It addresses both the substantial systematic uncertainty in modelling and the unknown ocean disturbances. To address the issue of disturbances in nonlinear route tracking, it is suggested to use a method involving the integration of SMC, fuzzy control, and adaptive control. The simulation results show that the proposed controllers are capable of keeping AUV path tracking satisfactory despite the fact that the AUV's velocity varies over the course of a trajectory. making use of an observer to accomplish AUV formation control in the water. To make optimal use of the observer, we linearize the AUV's translational motion with respect to the wave disturbances and discretize it to eliminate the effect of Coriolis and centripetal components. In this paper, all of the AUVs working together have access to the same set of error signals and orientation velocity. We evaluate SMC controllers with communication consensus and observers like SMO, SMC-EKO, and SMC-UKO to build AUV trajectories that coordinately follow the virtual leader. The global path planning problem is solved by contrasting the GA and GWO optimal solutions in three distinct environments: one with no obstacles, one with some obstacles, and one with many obstacles. It has been proven that GWO achieves lower path costs than GA does in situations with no obstacles, a few obstacles, and many obstacles.

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