Cooperative Swarm Behaviour For In Situ Underwater Environmental Measurements

Cedric Isokeit, Benjamin Meyer and Erik Maehle
University of Lübeck
Institute of Computer Engineering
23562 Lübeck, Germany
Email: {isokeit, meyer, maehle}@iti.uni-luebeck.de

***Abstract*—This paper presents an approach to perform comprehensive in situ environmental measurements in shallow waterbodies with the help of a swarm of small and flexible autonomous underwater vehicles (AUVs). To perform simultaneous measurements at different locations, the mission is automatically subdivided amongst the robots using a rule-based robot control architecture and special heuristics depending on internal robot states. This allows a significantly larger coverage of CTD measurements reducing costs on the one hand and minimizing the overall mission times on the other hand.**

I. Introduction

Due to constantly changing environmental conditions, physical and biological parameters of shallow waterbodies are affected in many aspects. Long-term effects can only be clarified by comprehensive series of measurements, which are realized by manual sample collections with the help of boats and divers. This is very cost-intensive and involves a large number of risks for researchers. Hence, autonomous underwater vehicles (AUVs) can help to provide the needed data and relieve the strain of various people in charge. A large number of robotic systems is available today, but most robots are too specialized or expensive in construction for commercial usage [1]. Usually, the AUVs operate as single vehicles like the most common REMUS AUV [2] or the Slocum Glider [3] for large scale ocean investigations. However, for the environmental monitoring of shallow waterbodies, the use of a swarm of small and inexpensive AUVs can serve to gather data in a simpler way. The OceanLab Data Driver [4] is such an approach to collect environmental data in a swarm of robots, but the system is still limited for submerged traces. This paper presents an approach to cooperative swarm behavior for more cost-effective in situ measurements at various positions at the same time. The described methods are then tested on our swarm AUVs MONSUN.

II. Swarm Behaviour

In order to realize an effective and efficient behavior of an AUV swarm some kind of swarm intelligence is needed. Therefore the swarm members need a communication channel for the purpose of forming a mutual knowledge base. For the communication a centralized approach was chosen to significantly reduce the needed amount of messages. Hence, this method is not only limited to high band-width WiFi communication but may as well be achievable by utilizing an acoustic channel. Acoustic communication provides far lower transfer rates but can be used by the AUVs while being submerged. The testet acoustic modems achieve a data rate of up to $13.9\,\mathrm{kbit/s}$ and operate in a frequency band from 18 to $34\,\mathrm{kHz}$ which enables an underwater communication to coordinate the swarm on the one hand and an online data transmission to the surface on the other hand. The swarm coordination and online data transmissions are explored in future work.

A. Communication

For a centralised communication, in the beginning one swarm member is designated as coordinator and is commissioned with the gathering of all needed data to assign tasks. To share information in a network of AUVs, the Echo algorithm of Chang [5] is utilized. The Echo algorithm can be applied to any connected topology of swarm members.

Independent of the used technology, every communication channel has its physical limitations. Especially signal range is a constraint of high interest for robot swarms. Dependent on robot positions and the used technology not all swarm members might be able to communicate with each other. Figure 1 illustrates some examples of topologies. In the upper left corner, all members are able to communicate directly with each other. The formation in the upper right shows robots that are following their predecessor. If the inter-robot distance is too large or in case of e.g. acoustic communication robot two shadows out the signal propagation coming from robot one or robot three, only a transitive communication is possible. In the lower example, a scenario for large swarms of AUVs is shown. Instead of operating in a single area, it might be beneficial to form groups to survey different territories. Here, two groups of AUVs are organized in diamond shaped formations. Within each formation all robots can communicate using direct routes. However, both groups can only exchange information using a relay.

In such topologies of robots with unique IDs a coordinator is then designated. The coordinator starts by flooding the network with explorer messages. The explorer messages are used to distribute information to adjacent AUVs in the topology. The explorer message is then relayed until the

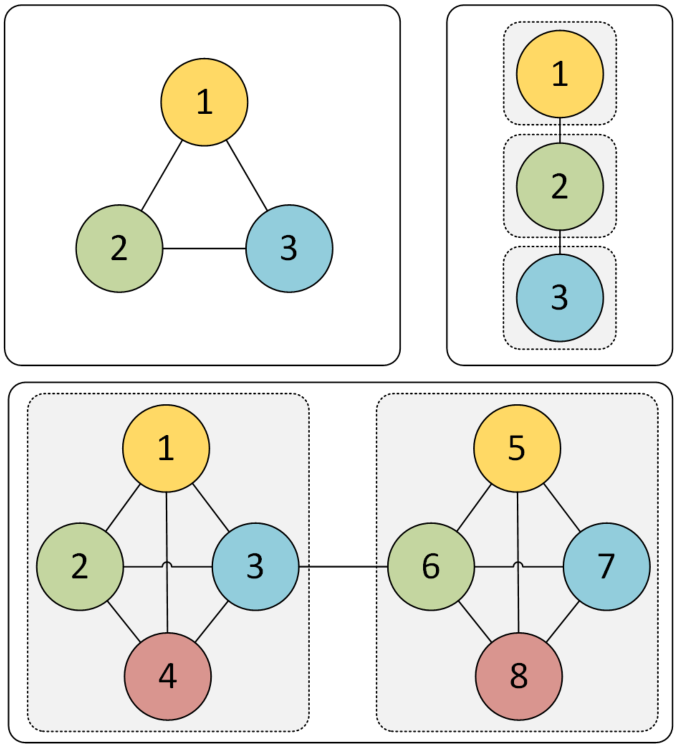

Fig. 1. Three examples of possible swarm topologies. Up left all members are interconnected, while in the upper right the distance only allows a transitive communication. The lower example depicts two interconnected groups that can only communicate via a relay.

external vertices of the topology are reached. Then the eponymous echo messages are used to send robot state information as a vector back to the coordinator. Each AUV provides its own data. The robot state can include data like current GPS coordinates ((x, y)), battery level ($charge$) and the equipped payload of sensors (N) for each AUV. Upon receiving the completed robot state vector the coordinator can allocate tasks to each member of the swarm based on this mutual knowledge base.

Another interesting aspect of swarm robotics is fault tolerance. The echo algorithm can as well be used as a selection algorithm to designate a new coordinator in cases of outage. The AUV that detects the outage of the coordinator, initiates the Echo algorithm by sending its unique ID. AUVs are aware that they lost the selection process once they receive an explorer message with a higher priority ID than their own. Alternatively the explorer messages are ignored when having a lower priority. The initiator has won the selection when receiving echo messages from all adjacent robots.

B. Mission Allocation

The allocation-rules of tasks described hereafter are for a specific mission type. For a given set of GPS coordinates, in situ measurements are to be conducted. For a single AUV this results in a travelling salesman problem for finding the optimal sequence of waypoints. When using a swarm of AUVs an additional constraint can be introduced. Mission time should be minimized while balancing the battery level of each AUV. The different tasks of the mission need to be allocated to the swarm members in a way that the mission is solved most efficiently. By additionally balancing the battery levels instead of just reducing total mission time, it is guaranteed that for further missions a maximum number of AUVs is still available. Otherwise, it might be possible that the battery level of a few AUVs is reduced drastically as they might be always the optimal choice for far away waypoints in hindsight to the time constraint. This problem is very similar to the knapsack problem. There is however no polynomial-time algorithm to solve this problem and it should be considered that robot processing units are often limited in computational power. Hence, a heuristic is used to get feasible solutions with minimal computational complexity. The heuristic function, as seen in equation 1, is calculated for all given GPS coordinates of a set of waypoints where measurements are to be taken and for all AUVs separately. The AUV with the lowest value of the function H_{MONSUN} for a measurement point wins the selection. For a specific point the sensor payload, the distance to the AUV and the battery level are considered. The payload N is a boolean indicator for the coordinator if the AUV is able to take all required measurements. This way AUVs without the needed equipment are not considered and can fulfill tasks at other waypoints. The distance $dist$ is multiplied with the inverse of the battery level $charge \in [0, 1]$. Fully charged AUVs are therefore assigned further distanced waypoints, balancing out the battery level of the swarm.

$$H_{MONSUN} = \begin{cases} undefined : N = False \\ dist \cdot (1 - charge) : else \end{cases} \tag{1}$$

An allocation of AUVs simply based on this heuristic is far from optimal, as this is a greedy approach that does not consider how the waypoints are positioned relative to one another. As an example an AUV is placed right between two measurement points and has the best heuristic values for these two but will then have to travel the maximum distance between these two points. A second AUV has an assigned target very close to one of these two points and should cover both to save mission time. Therefore, it is meaningful to subdivide the waypoints in clusters with minimal inter-point distances. By assigning the clusters to the AUVs instead of single points the traces can be further optimized. A classification of the measurement points can be achieved with pattern recognition and machine learning methods. A Principal Component Analysis (PCA) [6] without the final transformation of the data set already provides profound insights.

$$m_X = \frac{1}{N} \sum_{i,j=1}^{N} (x_i, x_j) \tag{2}$$

$$X_{me} = X - m_X \tag{3}$$

The PCA is a method to emphasize variety and highlight patterns in a data set X. In a first step the arithmetic mean m_x

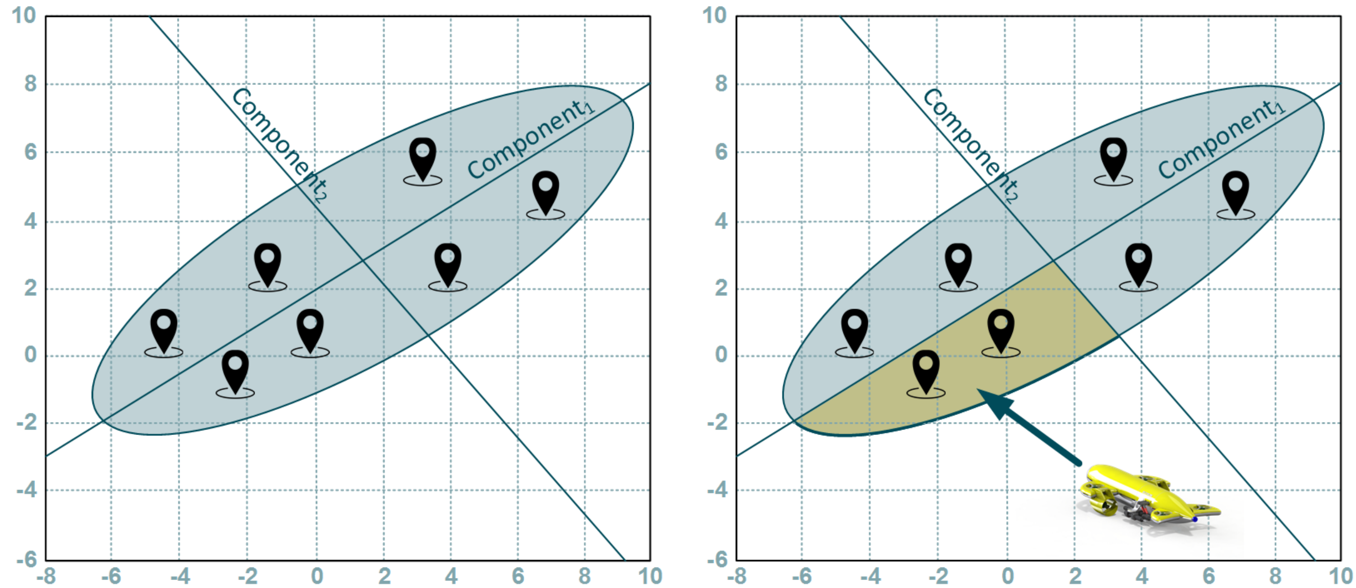

Fig. 2. An exemplary data set of seven points is given where measurements of environmental parameters are to be taken. On the left principal component one is pointing in the direction of the largest variance. Principal component two is orthogonal to the first and the ellipse is indicating the underlying statistical distribution. On the right the result of the projection of the waypoints onto the principal components can be seen. The set of points is subdivided into four clusters. A MONSUN is shown to be allocated to the lower left cluster.

for the features is calculated and the data set is then mean-freed, as shown in equation 2 and 3.

$$Cov(X, X) = E[(X - E(X))^2] = Var(X) \tag{4}$$

Next the data set is considered to be a statistical distribution with X being a real and integrable random variable. Therefore, the first moments $E(X)$ and $E(XX)$ exist and by these conditions the covariance matrix in equation 4 can be computed. The diagonal of the covariance matrix displays the variances in x and respectively y direction while the off-diagonal represents correlations. The goal is to find vectors with the biggest variance freed of any correlation. Therefore, a projection

$$\vec{v}^T COV(X, X)\vec{v} \tag{5}$$

needs to be found where the projected variances are as large as possible. An easy solution is solving the eigenvalue problem for the data set. By definition of the Rayleigh quotient, the maximum of such a projection is obtained by setting $\vec{v}$ to the largest eigen vector. Hence the biggest eigen vector is always pointing in the direction of the highest variance. Thus, the second largest eigen vector is orthogonal to the first. The direction of the highest variance also means that data points are furthest away from each other. Figure 2 depicts a set of points of interests on the left. The surrounding ellipse indicates the underlying statistical distribution for the PCA. The principal components are then pointing in the direction of the highest variances.

Dividing the data set along the largest variance is beneficial for task allocation. Therefore, the second moment is providing information about the relative positioning of points. Points in the respective subsets are much closer to each other than to the other subset. The smaller eigen vector can then be used as a classification line. Analogue to a perceptron classification rule all data points are projected onto the smallest eigen vector as shown in equation 6, yielding a binary classifier.

$$y = w \cdot x^T - \theta = (w_0 \cdot x_1 + w_1 \cdot x_2 + ... + w_n \cdot x_n) - \theta \tag{6}$$

For $y > 1$ the data point will be assigned class 1 and accordingly for $y \leq 0$ the class -1. θ refers to the displacement from the origin and is equal to zero, because the mean was subtracted in the first step and the data set is already centered around the origin. Figure 2 shows the classification line along the smallest variance for an exemplary data set on the right. Projecting the points onto the boundary will therefore yield a subdivision into two point clusters that can be assigned to different AUVs. When the mean position of a sub-set is used for the heuristic the computational cost is reduced to two per robot.

Two clusters can be easily allocated to two AUVs. For a third AUV the cluster with the most data points will be divided again using the same method, yielding three clusters. As shown in Figure 2 the left subset with four waypoints is split up and a MONSUN is assigned to the lower two waypoints. By recursively applying the PCA approach to each cluster, a number of clusters equal to the total number of waypoints can be generated. Within each cluster the AUV needs to minimize the traveled distance. This optimization problem is equal to the travelling salesman problem but for small enough sub sets still

Fig. 3. The AUV MONSUN in its base version features small size and high agility. Four brushless motors in the fins for vertical and two motors for horizontal propulsion allow MONSUN to control its pose very accurately.

feasible. Even greedy strategies can provide satisfying results on very small sub sets.

III. THE MONSUN UNDERWATER ROBOT

For all tests and evaluation of the beforehand described methods, MONSUN AUVs developed by the University of Luebeck are used. The MONSUN AUV is built in a modular forward-looking way to be used in a large number of possible tasks in the field of environmental monitoring. With a comparably small size of $60\,\mathrm{cm}$ in length and a diameter of $10\,\mathrm{cm}$, it features high agility and manoeuvrability due to six brushless motors [7]. This base version of MONSUN is displayed in Figure 3.

The ROS-based software architecture [8] for MONSUN is structured in three layers to strictly separate the control system, tasks and mission planning from each other. The modular design of ROS and this chosen architecture allows for easy adaption of the software for a specific task. Different robot behaviors are easily implemented on the one hand and on the other hand the publisher/subscriber structure allows for simply implementing higher levels of cooperation between the robots when using communication mediums like WiFi. For other mediums like acoustic communication there is only need for suitable middle-ware.

Furthermore, the robot contains an expansion set with additional sensors like a water sample extraction module or a professional CTD sensor to adapt to various deployment scenarios [9]. Currently there are five robots and first long-term measurements in shallow inland waterbodies and the Baltic Sea to improve the swarm behaviour have been performed. Two AUVs have taken part in project Clockwork Ocean [10] and provided data on submesoscale eddies in the Baltic Sea. In Figure 4, two modified MONSUN AUVs are displayed. An extra metal frame above the robot allows for easier deployment and recovery from ship and the antenna increases WiFi communication range at surface level. The robots use Wifi to exchange mission critical data like GPS positions, battery level and used payload. The payload is mounted under the AUVs. For the tests a CTD48 sensor [11] is used to provide basic oceanographic or limnological parameters like depth, temperature and conductivity.

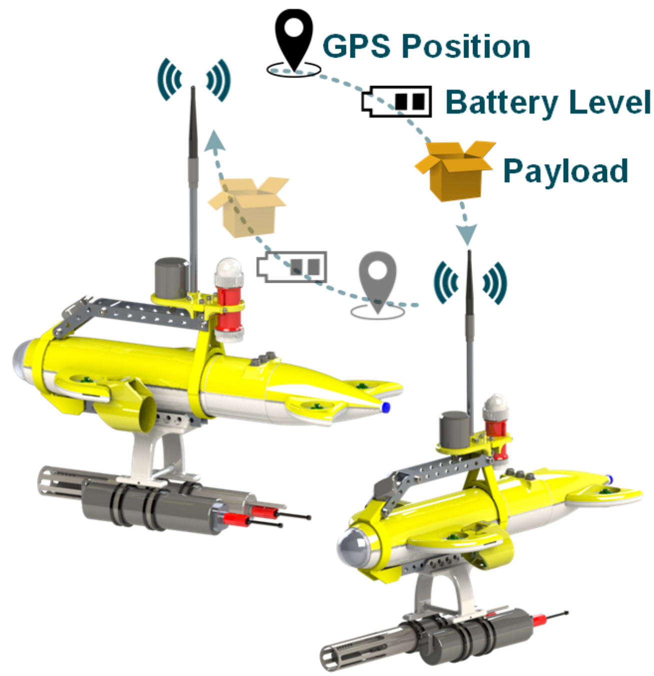

Fig. 4. The here shown MONSUN AUVs are modified for use in the baltic sea. The extra metal frame allows for easier deployment and recovery and the antenna increases communication range at surface level. As payload a CTD sensor and an acoustic modem are mounted below the robots. The MONSUN AUVs exchange GPS positions, battery level, and payload of sensors via WiFi.

IV. EVALUATION

The evaluation of the approach will be conducted using two MONSUN AUVs. For a specific mission scenario a local waterbody close to the University of Lübeck was chosen. In total four in situ measurements of environmental parameters have to be taken at different GPS coordinates. When a waypoint is reached the AUV is supposed to collect data for a time frame of $30\,\mathrm{s}$ at the position before navigating to the next point of interest. In Figure 5 the area with the four targets is displayed. In a first step a single MONSUN is given the task to survey the four target points as a reference value for the swarm based approach. The ideal round trip distance from the starting point is approximately $55\,\mathrm{m}$. With a chosen average velocity of $0.3\,\frac{\mathrm{m}}{\mathrm{s}}$ or $0.58\,\mathrm{knots}$ and a measurement time of $30\,\mathrm{s}$ at each point the total mission time is as follows:

$$T_{mission} = \frac{55\,m}{0.3\,\frac{m}{s}} + 4 \cdot 30\,s \approx 303\,s \qquad (7)$$

In the next step, a second AUV is deployed to assist the first one. After the designation of a coordinator AUV, the two swarm members exchange data via WiFi connection at the surface. Based on the collected information the coordinator assigns each swarm member a set of two points of interest. The traces of the AUVs are depicted in the colors blue and green. The AUV taking the green trace is assigned point one and two and is equipped with a Xsens MTi-G-700 IMU as well as an external GPS antenna for navigation. The positional accuracy at the target points is within range of two metres. The total track length for this MONSUN is now reduced to a length of $31.4\,\mathrm{m}$. The second AUV surveying the points three and four is equipped with an older version of the IMU and an internal GPS antenna. While moving, the GPS antenna is thus often covered with a layer of over washing water reducing the precision of the navigation greatly. The positional accuracy at the targets is still within a radius of $5\,\mathrm{m}$. The traversed distance measures at $34.6\,\mathrm{m}$. For the same measurement time of $30\,\mathrm{s}$ the total time of the mission is $173\,\mathrm{s}$ when using two AUVs. In comparison to the time of $303\,\mathrm{s}$ for a single robot, two robots were able to complete the same task in $57\,\%$ of the time.

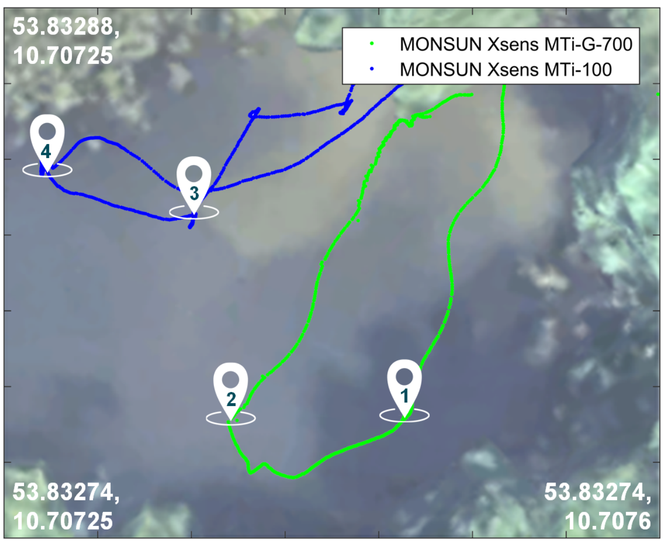

Fig. 5. Specific test scenario with four points of interest in a local waterbody near the University of Lübeck. The points are subdivided into two subsets and allocated to the AUVs.

With either higher measurement times at the points of interest or greater inter point distances this margin increases even more. The MONSUN AUVs are not only able to complete given missions considerably faster, but the use of multiple robots offers a degree of redundancy. Even when members of the swarm experience temporary suspension of service, the mission may still be completed by the other swarm members. In case of coordinator failures, the other members can designate a new leader independently using the selection echo algorithm.

For higher measurement times a plot of measurements is given in Figure 6. Upon arriving at a waypoint the AUV slowly descends to a depth of $4\,\mathrm{m}$ on the spot. After five minutes of measurement, MONSUN surfaces quickly and heads to the next waypoint. The data is collected with the CTD48 sensor providing high precision measurements of basic oceanographic or limnological parameters.

In the first plot the descend of the AUV can be seen in the gradual change of the depth value. Furthermore temperature and conductivity values are plotted for each depth level over the course of the five minutes. There is an obvious correlation between the three plots. But there are also indications for thermoclines in the temperature plot. At the depth of around one metre the temperature value hits a plateau before falling almost half a degree of Celsius at the depth of two metres. From these basic parameters additional features can be derived. Sigma-T for example is a quantity used mostly in oceanography to measure the density of seawater at a specific temperature. Another important parameter is the the speed of sound underwater. This variable is needed for accurate acoustic submarine-measurements.

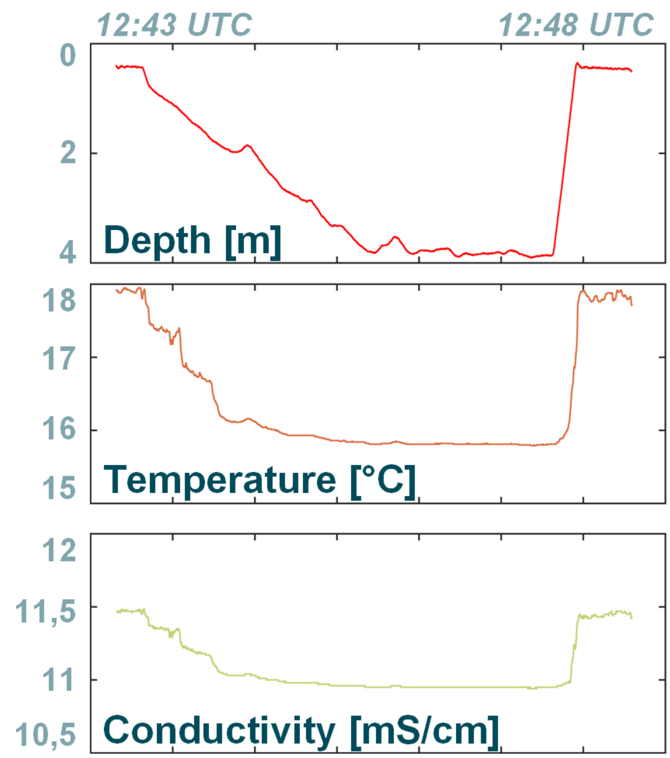

Fig. 6. After reaching the point of interest the MONSUN AUV starts slowly descending to a depth of $4\,\mathrm{m}$ as can be seen in the first plot. After $5\,\mathrm{min}$ of measuring parameters the AUV quickly surfaces and navigates to the next waypoint. The plots of temperature and conductivity show a correlation to the depth. The temperature curve furthermore indicates a possible thermocline at the the depth of around one metre. At two metres a sharp drop in temperature of around $0.5\,^{\circ}\mathrm{C}$ can be observed.

V. CONCLUSION

In this paper, a swarm-oriented approach for in situ underwater measurements was described. Due to the low amount of needed messages, the presented Echo algorithm is applicable for surface-based and underwater communication alike and can also be used as a selection algorithm to provide system recovery options. The heuristic in combination with a PCA-based binary classifier can be run with low computational power and delivers efficient waypoint allocation for the swarm members. The approach is highly scalable to the number of swarm members without increasing problem complexity. In the test scenario in Figure 5, the path depicted in blue was $34.6\,\mathrm{m}$ long and the other $31.4\,\mathrm{m}$. For a measurement time of $30\,\mathrm{s}$ at the waypoints, the mission was completed after $173\,\mathrm{s}$ with two AUVs. A single MONSUN had to travel $55.2\,\mathrm{m}$ and completed the mission after $303.3\,\mathrm{s}$; an increase in mission time of $57\,\%$. With higher measurement times as seen in Figure 6, this margin increases even more. The CTD48 sensor yields high precision measurements for oceanographic or limnological purposes. It is possible to detect thermoclines and compute water density along the complete water column. This way two water parcels can easily be compared by e.g. oceanographers.

Besides being able to complete missions faster, the use of multiple robots provides redundancy. In the case of failure of one AUV, the mission will not fail and can be completed by the other swarm members. For future work possibilities of the use of acoustic communication are explored. Acoustic distance measurements could aid in underwater navigation and the possibility of live transmission of measurement features can help scientists survey areas. The mission can then be adjusted accordingly to concentrate specifically on points of interests.

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