LOCALIZATION IN AN AUTONOMOUS UNDERWATER MULTI-ROBOT SYSTEM DESIGNED FOR COASTAL AREA MONITORING

Zhongliang Hu, Eemeli Aro, Tapani Stipa†, Mika Vainio, Aarne Halme

Finnish Center of Excellence in Generic Intelligent Machines Research,
Aalto University School of Science and Technology
P.O. Box 15500, FI-00076 Aalto, Finland
{zhongliang.hu, eemeli.aro, mika.vainio, aarne.halme}@tkk.fi
†Marine Hydrodynamics, Finnish Meteorological Institute,
Erik Palmenin aukio 1, P.O. Box 50, FI-00101, Helsinki, Finland
tapani.stipa@fmi.fi

Abstract: In this paper we present an multi-robotic system for underwater exploration, specifically for coastal seas. The novelty of this system is its enhanced performance in underwater localization using underwater acoustic ranging and data transfer between the floats. This process is not dependent on any fixed infrastructure, which is usually a requirement for such missions. An algorithm is implemented in the floats for underwater localization, based on an Extended Kalman Filter. Extensive real scenario simulation test results are presented.

1 INTRODUCTION

The value of services provided by the coastal seas, including estuaries, to the human welfare is estimated to be higher than those of terrestrial or open ocean systems (Costanza et al., 1998). The relevant spatial and seasonal scales for biological variability are often related to hydrophysical events; these are mostly unpredictable and practically impossible to cover by traditional monitoring with sparse sampling.

Autonomous underwater multi-probe system for coastal area / shallow water monitoring (SWARM) was an EU-funded (FP5, 2003-2005) project aiming to design, implement and test a multi-robot system that could measure local and transient biological and physical variability in the Baltic Sea and similar areas at the scale relevant for single events.

Based on the initial ideas and hardware designed and built during the SWARM project, the Finnish Center of Excellence in Generic Intelligent Machines (GIM) has continued the related research. As one of the results, a localization method has been developed that requires no additional infrastructure, fixed beacons or expensive inertial units, while producing accurate real-time location estimates for the members of the system. The method is based solely on underwater inter-robot acoustic communication and occasional GPS fixes while on the surface. It is worth mentioning that the internal intelligence which is essential for the units to navigate and survive in the dynamic and hostile underwater environment makes the units stand out from mere buoyancy floats to intelligent underwater robots.

In this paper, the main features of this system working in an extremely challenging environment will be first briefly introduced. Then, the main topic of this paper, i.e., a novel localization approach will be presented and verified with suitable tests. Finally, some conclusions are drawn and some information regarding the future work will be presented.

2 SYSTEM DESCRIPTION

The scientific objective of the SWARM project was to design, implement and test a novel highly redundant underwater monitoring system for shallow water areas (Vainio et al., 2004). The system consists of multiple homogenous, robust and easy to use underwater robots (autonomous intelligent profiling floats) that can perform two week missions autonomously. The floats control their buoyancy but move otherwise freely with the water flows. They communicate with the control station via Iridium satellite communication and use inter-robot acoustic ranging and commu-

nication for localization and data exchange. In addition to measuring the standard variables (pressure, temperature, conductivity), the system observes certain algal groups with a novel fluorometer.
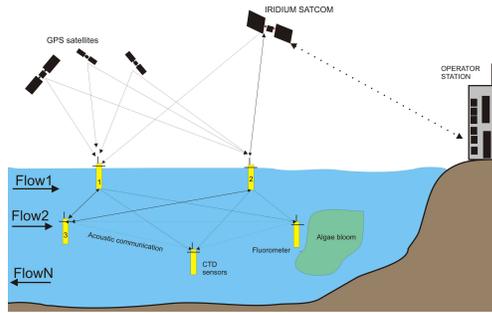

Figure 1: The general description of the SWARM system.

The diving profile of the floats was selected based on two main issues: to enable the system to measure the key environmental parameters from the main areas of interest and to support the proposed localization method. It also matches the standard profile used by Argo floats globally, but of course with shallower depths (Davis et al., 2001).
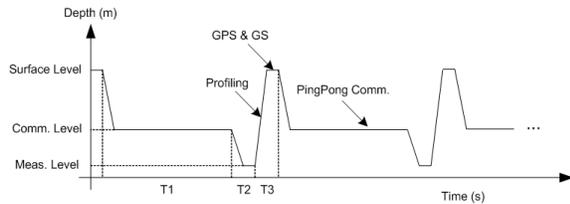

Figure 2: Diving profile of a unit.

T1: Waiting time. The float spends most of its time waiting on this level. The benefit of this is such that the float does not need to stay on the surface all the time but by taking advantage of communication it can still keep a track of its location during the mission.

T2: Diving time. When T1 expires, the float will start to dive to a deeper level and wait there for the start of profiling.

T3: Profiling time. After T2 expires, the floats ascents to surface, during which time it takes CTD(conductivity, temperature and density) profile. When the float reaches the surface, it gets a GPS fix and contact the operator station for possible commands and reports data.

3 EXPERIMENTAL SETUP

During the EU-funded phase, the functionality of each of the subsystems were tested separately before final integration into a prototype. Major part of these tests were carried out in Gulf of Finland on the south coast of Finland. In addition to the real system, a MATLAB based simulator was designed at an early phase of the project mainly for the testing of localization algorithms. After the end of the EU funding a more sophisticated simulator was constructed and used for the testing presented in this paper.
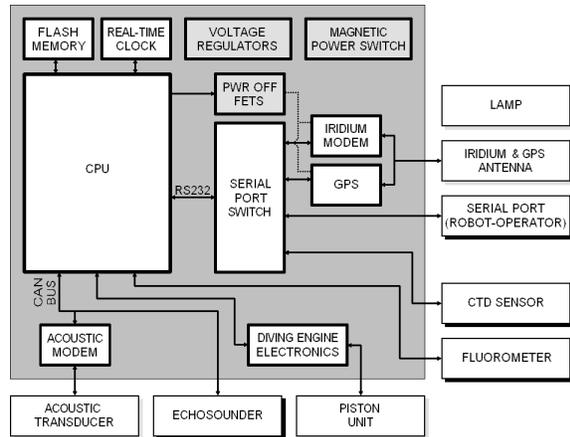

Figure 3: Subsystems shown in a block diagram.

A simplified block diagram shown in Figure 3 illustrates that the developed robotic prototypes are full-blooded autonomous profiling floats which are equipped with extensive repertoire of environmental sensors. Furthermore, they possess certain level of intelligence, which is required to survive autonomously in a dynamic and hostile coastal waters.

3.1 Physical Realization

The main physical output of the SWARM project was four 3rd generation functional floats ready for open sea testing. These floats have since been extensively modified and tested in the lab. Full-scale tests are expected to start from summer 2010. See Figure 4.

3.2 Simulator

A new simulator is implemented as an attempt to produce a near-realistic simulated environment for autonomous floats. The simulator uses a server-client architecture, with the environment as a server to which each float connects. Specialized clients may also connect to the environment to act as ground stations or data display/logging agents. Time in the simulator advances at a multiple of real time. The interfaces available to a program acting as a simulated float are modeled to match those of an actual float,

Figure 4: Available physical floats (own by SWARM consortium). Floats are around 2 m tall and weigh approximately 40 kg.

including simulated sensor errors and measurement time delays. This allows for hardware-in-the-loop testing using the real float hardware, with each sensor connected using a serial cable to an external computer running an interface program connected to the simulated environment.
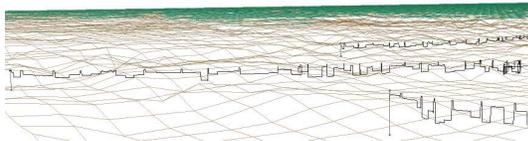

Figure 5: Snapshot of the developed simulator.

The simulator components use GIMnet (Saarinen et al., 2007) to communicate, allowing each program to run on a separate networked computer if required. The architecture is designed to scale, and can simultaneously model hundreds of floats at a simulation speed far in excess of real time. The simulator can make use of data from anywhere in the world, provided that bathymetry and three-dimensional time-variant salinity, temperature and current vector information is available to some precision; intermediary values will be interpolated. The data used for the tests presented here is from the BalEco ecosystem model of the Finnish Institute of Marine Research (currently Finnish Meteorological Institute).

4 FLOAT LOCALIZATION

The core element of a SWARM unit positioning system is a GPS receiver, which is included in each of the robots. When on the surface, a unit gets its position from the satellites. The frequency of these GPS fixes must be considered carefully. They will naturally always bring much needed fresh and accurate information to the system, but on the other hand, they force the units to come to the surface which consumes energy and increase the possibility of being hit by a passing boat. In any case, after the GPS fix, the inter-robot acoustic communication system between robots is then utilized in positioning the underwater units.

It is essential to relate the measurement data that the floats have gathered underwater with the geographical coordinates where they have been measured. A conventional float profiling operation, as shown in Figure 2, gives reasonable results for a series of measurement when the float comes back to the surface from the deep depth, since such surfacing happens in a quite short time and the currents affecting this movement are negligible. However, this movement only gives a vertical series measurements at a given location. We are more interested in the sea conditions in a larger area, including prevailing sea currents. One approach for this can be found in (McFarland and Honary, 2003).

4.1 Baltic Sea

Shallow seas pose specific problems for robotic ocean instruments. They are often strongly stratified, turbid and have vibrant maritime activities. The bottom is soft, to the extent that it may have adhesive powers on instruments that land on the bottom. Figure 6 shows an example of the complex vertical structure of temperature, salinity and fluorescence, with almost unnoticeable physical features that nevertheless have their impact on the biological situation.

The spatial scales of motion are often small in the horizontal direction as well. Therefore, the state of motion in one place is not a very good predictor of the state some kilometers away. These factors make it harder to observe shallow seas with robotic instruments than the ocean. There should be a large number of robotic instruments to capture the spatial variability, yet the loss rate of robotic instruments in shallow seas is expected to be significantly larger than in the blue oceans, where a typical Argo float may survive 3-5 years.
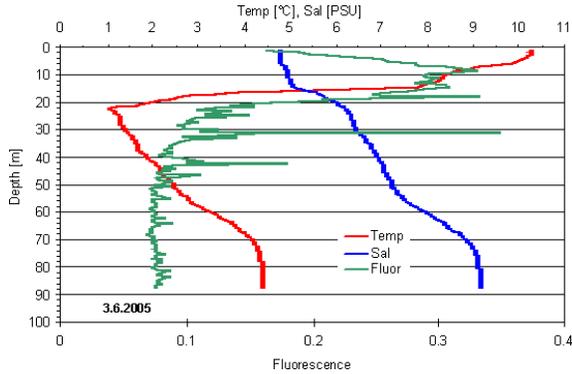
Figure 6: Complex vertical structure of temperature, salinity and fluorescence against depth in the Baltic Sea.

4.2 Acoustic Communication

The range and reliability of underwater acoustic communication is affected by a number of factors, including signal attenuation, noise, reverberation and sound channeling. A transmitted signal will be reflected from the surface or seabed and interfere with the direct path signal. Variations in the temperature and salinity at different depths will result in variations in the speed of sound, which will influence the path of the signal. The sound speed profile for the Baltic Sea is in fact conducive to the formation of a sound channel, a depth at which acoustic signals will reflect internally due to a minimum in the speed of sound. This channel is present mostly during the summer, and varies in depth from 20m to 80m. Using this sound channel, floats in the Baltic Sea can theoretically achieve communications and ranging over distances of up to 10km. In addition to communication, acoustic transmissions may also be used for ranging, by tracking the time of flight of messages. The SWARM floats implement a ping-pong type scheme for measuring the round-trip travel time between floats.

In this paper we use a simple linear model of the probability of construction a communication between drifters. When two floats are at immediate vicinity they have a near guaranteed communication probability, whereas at around 6 kilometers distance, the probability of having a communication channel between two floats falls almost to zero. To determine the position of one float from another, a ranging signal is used. In effect, the float transmits a message and waits for the reply from the receiving float.

A unit that has been on the surface sends its newly obtained GPS position information through acoustic modem once it has reached the defined communication depth and it is its time to communicate. Knowing

their own estimated positions and past trajectories, the underwater units can reduce the uncertainty of their position based on this information. A positional accuracy in the scale of hundreds of meters is acceptable in this application. The biggest advantage of this positioning system is the fact, that there is no need for any additional positioning devices, e.g. fixed acoustic buoys used in (Akyildiz et al., 2006; Dario et al., 2005).

4.3 Algorithms and Implementations

The Kalman filter is an efficient and robust recursive filter that estimates the internal state of a dynamic system from a series of noisy measurements. It can also estimate the variables which can't be directly measured (Welch and Bishop, 1995). In our case, this corresponds to the underwater sea current.

For this paper, the underwater localization estimation is based on an Extended Kalman Filter(EKF). The state variables are geographical positions of the units and the vectors describing the currents in the sea in different depth layers, while GPS fixes and distances between the floats through an acoustic ranging being the measurements. Note that in this particular case, we do not include the depth coordinate into the estimation as well as the vertical part of the sea current vector because the measurement of the depth itself is accurate enough. Since we can have a relatively good measurement of the depth from the CTD sensor, and taking the system propulsion into account is not beneficial. This arrangement will also reduce the complexity of the computation which is a limiting factor in the real system onboard.

First we start with defining the state and measurement vectors. The current vector at level j at position (x,y) at k time step of EKF:

$$F_j(x,y)(k) = [f_{jx}(k) \quad f_{jy}(k)]^T \tag{1}$$

In Section 4.1 we have described the basic situation for the Baltic Sea current and its unique character of being layered. Thus, the environment can be thought as series of layers that each have a flow vector representing the sea currents, which slowly varies from one location to another. The units are located at these layers as shown in Figure 7.

To better estimate such phenomena, we divided the sea current vectors into three layers. In addition to limit the computation complexity, we also choose this number to correspond to the diving profile as shown in Figure 2. The flow vector at position (x,y) at k time step of EKF is defined as:
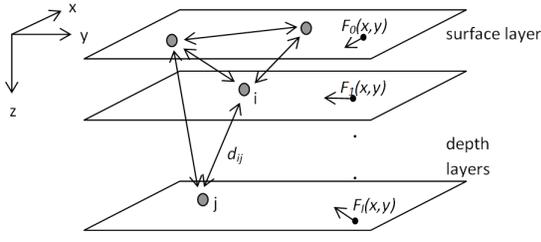
Figure 7: The units are located at layers that have different flow vectors.

$$F_C(x,y)(k) = [F_1(x,y)(k) \ F_2(x,y)(k) \ F_3(x,y)(k)]^T \tag{2}$$

Position of a float at position(x,y) at k time step of EKF:

$$P_j(x,y)(k) = [x_j(k) \ y_j(k)]^T \tag{3}$$

In this project, we set EKF update rate to $\Delta t = 5 minutes$. Considering the real data collected by Finnish Marine Research Institute, we can assume the current vector is changing slowly both with respect to horizontal location and time. The current dynamics is modeled as:

$$F_C(k) = F_C(k-1) + v(k) \tag{4}$$

where $v(k)$ is the system error of the current.

Let's define the extended state Vector of EKF at time step k:

$$\tilde{X}(k) = [P_1(k) \ P_2(k) \ ... \ P_n(k) \ F_C(k)]^T \tag{5}$$

The corresponding extended state equation:

$$\tilde{X}(k) = A(k)\tilde{X}(k-1)$$
$$= \begin{bmatrix} I & \Delta T \\ 0 & I \end{bmatrix} \begin{bmatrix} P(k-1) \\ F_C(k) \end{bmatrix} \tag{6}$$

Here, system matrix A is updated each time according to the depth layers (DL) of respective floats. In other words, the prior prediction of the float location is updated only by the current vector in its present layer.

The example ΔT Matrix for 3 floats, while float 1 in depth 3, float 2 in depth 1, float 3 in depth 2:

$$\Delta T = \begin{bmatrix} 0 & 0 & \Delta t \\ \Delta & t & 0 \\ 0 & \Delta t & 0 \end{bmatrix} \tag{7}$$

All the floats maintain a depth list of all the known floats. Since the measurements that these floats get are different, even having the same equations running internally, they have different estimations of the state vector. Since the floats spends most of its time in the waiting layer, when there is no depth update from the others, they are assumed to be in the waiting layer (check Figure 7).

Measurement equation:

$$Z(k) = [P_{GPS1}(k) \ P_{GPS2}(k) \ ... \ P_{GPSn}(k)$$
$$d_{12}(k) \ d_{13}(k) \ ... \ d_{(n-1)n}(k)]^T \tag{8}$$

Expected measurement:

$$h(\tilde{X}(k-1)) = [P_1(k) \ P_2(k) \ ... \ P_n(k)$$
$$\|P_1(k) - P_2(k)\| \ \|P_1(k) - P_3(k)\|$$
$$... \ \|P_n(k) - P_{n-1}(k)\| \ ]^T \tag{9}$$

To linearize h with respect to X for each update step:

$$H(k) = \partial h(\tilde{X}(k-1))/\partial \tilde{X}(k-1) \tag{10}$$

The overall running EKF for k time step:

$$\tilde{X}(k) = \tilde{X}^-(k) + K_k(Z(k) - h(\tilde{X}^-(k))) \tag{11}$$

where the Kalman gain k is calculated in a standard EKF formula.

Note that in reality, it is rarely the case that the float will get all the distances from all the other floats and the distances between them. And it is only occasionally when the float has a GPS fix on the surface and gets GPS information from the others. In such case the EKF automatically assumes those measurements are missing and therefore not take them into account while updating the state variables.

5 TESTS AND RESULTS

The simulated environment contains the flow vectors and other environmental data that affect the positions of the floats. The actual positions of the units are maintained by the simulator, but they may be measured by the floats only in a way that is similar to the real world, i.e. only the units that are on the surface know their positions, and distances between floats are only measured in seconds of sound travel time. The user can control whether the units know only the distances from the unit itself to other units, or if they know all the distances between all pairs of units. Every unit contains a Kalman Filter that estimates the positions of the units. The estimation is based on the model that utilizes both the measured distances between the units and the measured positions of the

units while on the surface. The real and the estimated positions can be visually tracked and compared in real time. The following figures are the comparison result for a random chosen float in the system during their respective missions.

5.1 Turning vs. Line traveling

In an area where the current vectors change quickly, a float will typically make sharp turns. In such circumstances, its position estimates can be quite inaccurate. On the other hand, in a case where the currents are more homogenous, the float will follow a approximately straight line and its estimation is obviously better as time passes.

5.2 Test Configuration

The simulation test area is selected to be a bay area not far from the Finnish coast. The key parameters are set as shown in Table 1.

Table 1: Key parameters setting for Simulation.

Acoustic comm. interval	once/hour
Surfacing interval	4 times/day
Surfacing time	10 minutes/dive
Comm. level waiting time	5 hours/dive
Meas. depth waiting time	40 minutes/dive
Kalman filter update interval	once/5 minutes

These parameters are consist with the future real test parameters.

5.3 Baseline Estimation

As a baseline for estimating the quality of the localization method, we use an alternative position estimate which makes no use of acoustic ranging or communication, and instead assumes the current position to match the latest GPS position fix. See Figure 8 for demonstration.
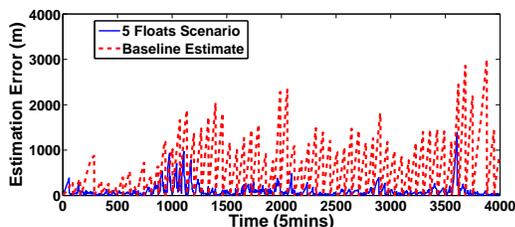

Figure 8: Estimation error for 5 floats randomly deployed within 50m radius area with the the same diving profile. Error is in Euclidian distance between the estimated and real position.

5.4 Data Information Exchange

High bandwidth acoustic data exchange between floats in the Baltic Sea is extremely difficult. It is especially true when the floats are not always staying in the communication layer, which does not even exist in some cases. In Figure 9, we show the results from both only acoustic communication enabled scenario and acoustic & data exchange enabled case. Both of them follow the communication probability model explained in Section 4.1.
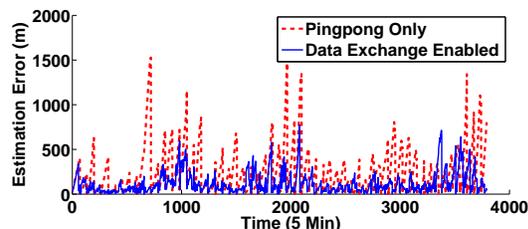

Figure 9: Estimation error comparison between acoustic ranging only and data exchange scenario. (5 units that deployed in a 50m radius area with same diving profile)

5.5 Deployment Strategy

To deployment pattern of the float is an important factor that has a considerable effect on the outcome of the whole mission. When the drifters are deployed within a small perimeter (radius 50*m*), for example from an anchored boat, the high probability of exchanging information will increase the possibility to have accurate position estimates. It is especially important for the drifters at their initialization phase. Since they will experience almost the same current vectors throughout their journey, which makes them most likely remain close to each other throughout the mission. The downside is of course the fact that the system can only obtain data from a small proportion of the area.

When deployed in a large area (radius 2*km*), the floats disperse nicely during the mission. However, the probability for the floats to get extra information(information besides its own GPS fix when surfacing) is very low. It is so low that their estimation of respective location is of a similar level of the benchmark estimation which only rely on GPS fixes.

To comprise, one possible solution is to deploy floats into the water in a relatively small perimeter, and make their waiting depths slightly different. Since the current field in the Baltic sea is clearly layered, the current vectors they experience is different. By the end of the mission the floats drift nicely away

from each others (up to $6km$). Of course, one downside for this approach is that, in reality, the communication channel is correlated to a specific depth level, which will lower the probability of data exchange. See Figure 10.
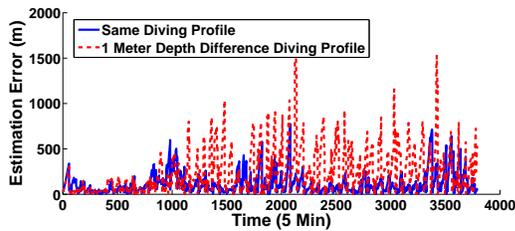

Figure 10: Estimation error comparison between 0m waiting depth(Same profile) difference against 1m depth difference deployment for 5 floats.

5.6 Current Estimation

One of the main target of the mission is to accurately measure the subsurface currents speed and directions. Usually this is of particular difficulty since the complex situation underwater is hard to be measured directly. With the help of acoustic inter-robot communication, we have achieved some promising results.

Figure 11 and 12 show the current magnitude and angle estimation generated by Kalman filter from the one randomly chosen float.
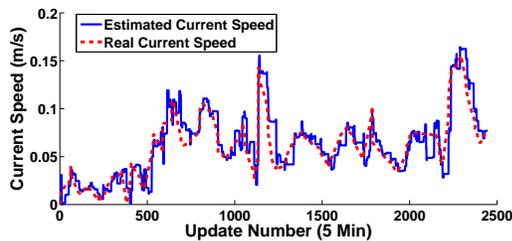

Figure 11: Current estimation magnitude error for 5 floats randomly deployed within 50m radius with the same diving profile.

There is a small lagging of the filter result towards the real environmental current data, which can be explained by the filter properties. However, the preliminary results are promising and deserve further research.

5.7 Float Numbers

Obviously, one of the most important factor is the number of floats in a given mission. During a mission, with a greater number of floats, there are more GPS
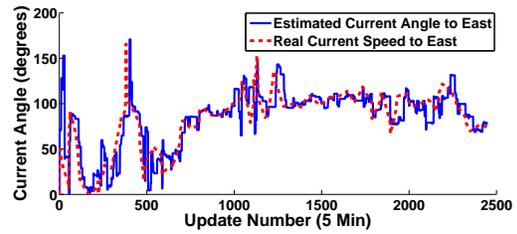

Figure 12: Current estimation angular error for 5 floats randomly deployed within 50m radius with the same diving profile.

fixes and distance measurements to share and there is a higher probability to gather such information from the communication between the floats. See Figures from 13, 14, 15.
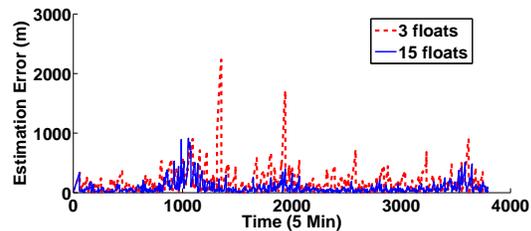

Figure 13: Estimation error comparison between 3 units and 15 units mission. Deployed in 50m radius area with 1 meter depth difference in communication level.
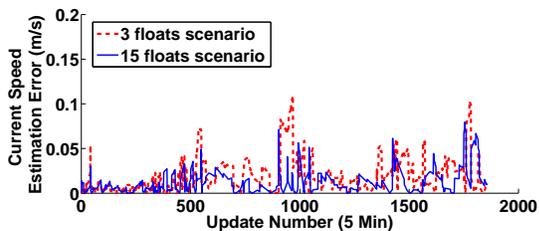

Figure 14: Comparison of absolute current speed estimation error between 3 floats and 15 floats scenarios. Both scenarios deploy within 50 meter radius and 1 meter waiting depth difference.

The number of floats in a given mission gives an interesting topic to research. The performance improvement also added a degree of difficulty and complexity for acoustic communication, data exchange via acoustic modem and the localization algorithm.
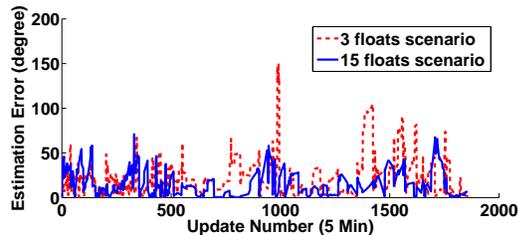
Figure 15: Comparison of absolute current direction estimation error between 3 floats and 15 floats scenarios. Both scenarios deploy within 50 meter radius and 1 meter waiting depth difference.

6 CONCLUSIONS AND FUTURE WORK

Multi-robot systems have a great inherent potential in various applications requiring localization and navigation capabilities. In this paper, we have shortly introduced a multi-robot system suitable for operations in the shallow water conditions near the coastline. The main contribution of this paper is the validation of our implementation of a localization algorithm in these demanding conditions. The obtained results, which are drawn from extensive simulations based on real case scenarios and environmental data, have proved the validity and effectiveness of our approach for the localization of these intelligent autonomous profiling floats.

However, there is much more yet to be explored in terms of our research. We will briefly introduce a better underwater communication channel modeling, in particular for the layered Baltic sea case. Further tests scenarios with different surfacing intervals, acoustic communication intervals and dynamic mission planning will be conducted. Later research will also include optimization between communication bandwidth, energy and reliability, data compression in data communication and other filtering algorithms. Real world robotic tests with renewed four unit system will be started in summer 2010 and they will further guide the future research.

REFERENCES

Akyildiz, I. F., Pompili, D., and Melodia, T. (2006). State-of-the-art in protocol research for underwater acoustic sensor networks. In *WUWNet '06: Proceedings of the 1st ACM international workshop on Underwater networks*, pages 7–16, New York, NY, USA. ACM.

Costanza, R., d'Arge, R., de Groot, R., Farber, S., Grasso, M., Hannon, B., Limburg, K., Naeem, S., O'Neill, R. V., and Paruelo, J. (1998). The value of the world's ecosystem services and natural capital. *Ecological Economics*, 25(1):3–15.

Dario, I. A., Akyildiz, I. F., Pompili, D., and Melodia, T. (2005). Underwater acoustic sensor networks: Research challenges. *Ad Hoc Networks (Elsevier*, 3:257–279.

Davis, R. E., Sherman, J. T., and Dufour, J. (2001). Profiling ALACEs and other advances in autonomous sub-surface floats. *J. Atm. Ocean. Tech.*, 18(6):982–993.

McFarland, D. and Honary, E. (2003). Flock distortion: A new approach in mapping environmental variables in deep water. *Robotica*, 21(4):365–383.

Saarinen, J., Maula, A., Nissinen, R., Kukkonen, H., Suomela, J., and Halme, A. (2007). Gimnet - infrastructure for distributed control of generic intelligent machines. In *Proceedings of the 13th IASTED International Conference on Robotics and Applications Telematics 2007*. The 13th IASTED International Conference on Robotics and Applications Telematics.

Vainio, M., Halme, A., Troshin, I., Stipa, T., Seppala, J., Pollehne, F., Bauerfeind, E., Haardt, H., Brault, P., Seube, N., Smerdon, A., Caine, S., Swale, B., and Hakala, A. (2004). Autonomous underwater multi-probe system for coastal area/shallow water monitoring (swarm). In *Proceedings of the EurOCEAN 2004 Conference*, Ireland. EurOCEAN 2004 Conference, Galway 2004.

Welch, G. and Bishop, G. (1995). An introduction to the kalman filter.