Underwater Robot Localization Using PC/BC-DIM Autoencoder

Umair Ali[1] and Wasif Muhammad[1]

[1]Dept. of Electrical Engineering and Technology, Gujrat, 50700, Pakistan
[1]eeumairali@gmail.com
[2]syed.wasif@uog.edu.pk

Monday 30th December, 2019

Abstract

Underwater robot localization is a challenging research topic because of the dynamic and unstructured nature of seabed environment. When vehicle is below the surface of water it is not possible to rely on Global positioning sensor (GPS) and other radio positioning systems . Here in one line it should be stated that fusion of difference sensors can be helpful because of above said reason..In case of fusion of multiple sensors Kalman filter can not deal with non-Gaussian noise and other parametric filters which have high computational cost . For underwater localization building an optimal fusion policy with low computational cost is an important research question. We proposed an autoencoder approach named as PC-BC/DIM which has the capability to fuse and approximate sensory information in an optimal way. Results have shown that our ~~filter~~proposed method outperformed all previous techniques using same sensory data.

Which other radio positioning systems?

parametric filters such as . . .

1 Introduction

Autonomous underwater vehicle (AUV) and remotely operated vehicle (ROV) are most commonly used for underwater operations. ROV is guided vehicle and is used specifically for sea inspection, maintenance and repairing purposes give space and use citep instead of cite (Grøtli et al., 2016). AUV is unguided vessel and uses for general purposes like research, defense and exploration without interference or semi-interference from external guidance (Miller et al., 2018). While performing search operations *e.g.*, looking for missing planes, ~~or~~ drowned ships, or ~~and~~ discovering ~~of~~ new species ~~or~~ and natural resources ~~are required to locate~~ self-localization of AUV is required. Collection of exploration data is meaningless if ~~we~~ an AUV can not ~~describe~~determine or estimate its ~~the~~ exact location ~~of vehicle~~ (Li et al., 2015). Self-l~~L~~ocalization plays an important role ~~in navigation to control~~ in control of a underwater robot navigation where it works as a feedback for correcting heading and location of underwater robot.

"where . . . underwater robot". Makes no sense!

Available technologies are good enough for territorial environment but not for underwater because of rapid attenuation of noise due to dynamic and unstructured nature of water (Paull et al., 2013). A big problem for ~~below~~ underwater localization is unavailability of GPS radio signals (Leonard and Bahr, 2016) because territorial communication is done using electromagnetic signals which does not work below the surface of water.

What? vechile self-localization? or navigation?

Follwing sentences closed in double quotes are poorly written! sometimes even sentences are incomplete. Rewrite these again in a better and comprehensible way.

"We can go for alternatives like acoustic and vision positioning systemsCorke et al. (2007). Vision based systems are needed some defined locations like some signs and landmarks to localizeAl-Rawi et al. (2017) otherwise there is no global location. Considering this acoustic position systems are more better choice for underwater localizationKhan et al. (2010) specially for unknown environment where there are no fixed landmarks. Instead to have a single expensive sensor it is better approach to have multiple low cost sensors. Combing them through fusion algorithms we can estimate the optimal location. Considering sensory information Doppler velocity log (DVL) works accurately below the surface of water and GPS is fine for near surface but in middle of deep sea there is always limitations**?**. Although, acoustic positioning sensors are there for local positioning information still sound travelling uncertainties are there**?**. "

1.1 Literature Review

Direct ~~values~~ measurements of inertial sensors contain high uncertainty because of underwater environment whereas in such environment ~~at the same time~~ acoustic systems ~~may~~ produce delayed measurements and abrupt noise. "For support inertial sensors are added to have more faster rate of location values but the noise of inertial sensors is also there. If we rely on only dead reckoning sensors like PanPan and Wu (2016) the problem of residual error will remain there that is main reason to have a global sensor. Their is need to fuse sensory information so we can represent them in one standard format"

Rewrite these double quoted sentences to make comprehensible.

. Mutisensory fusion for underwater localization is very essential need because of each sensor's limitation in deep water. A new challenge arises ~~Problem~~ in multisensory fusion ~~is~~ because of diverse~~ity~~ ~~of~~ sensors modalities ~~on the basis~~ and because of their different sample rates ~~of giving value~~ and frame of reference (Folkesson et al., 2008). Optimal fusion policy with low computational cost to eliminate abrupt noise of acoustic positioning system which comprises global and inertial sensors is open research questionChame et al. (2018).

If ~~we are~~

Too much usage we try to write sentences without using first form of person.

able to model the system below surface of water then there would not be any limitations for conventional fusion policies to estimate the current pose at given instant. Kalman Filter is famous for motion estimation (Azuma and Bishop, 1994) using uni-model hypothesis. In kalman filter based on the prior hypothesis probability of hypothesis of predicted state is estimated which is further corrected by measurements of sensory data. As underwater noise can not be modeled so unimodel estimations of Kalman filter can not return effective results. Extended Kalman filter is used for converting non linear system to locally linear (Keatmanee et al., 2013) by involving jacobian matrix which affects computational cost as well as it can not overcome abrupt noise of acoustic sensor. ~~If we go for~~ In case of non gaussian distributions ~~then~~ Particle filters are non linear models but have expensive computational cost because of probabilities distribution based estimation (Fox et al., 1999). Due to multiple hypothesis particle filter gives delayed results even when there is reliable sensory data. Least squares regression formulation presented in (**?**) saves the past states for posterior state estimation. Regression considers every sensor important to estimate the state although we can use linearly weighted regression to assign the weights of individual sensor based on its accuracy but sensors have diversity in accuracy in shallow and deep water. '

In some recent advancements regarding underwater localization researcher has proposed various useful techniques considering the dynamics of underwater environment. A visual odometry algorithm is developed for underwater robot localization (**?**) in which from the pictures features are extracted and matched for location determining. such image based location estimation is quite accurate although the problem we can face is delaying in recognition. Some bio-inspired work is presented demonstrating the location estimation just like a fish sense the flow rate under the water and using the predefined map the location can be estimated (**?**). Similarly based on mammals navigation DolphinSLAM (**?**) approach is presented which is appearance based localization method and in contrast to probabilistic methods low resolution sonars and images can be used for underwater localization.

For single onboard vehicle one approach to overcome noise is modeling of non-linearities by supervised learning (Fang et al., 2019) but this is suitable where system repeat patterns and task conditions remain almost similar between training and execution time. To identify the reliability of acoustic positioning sensor is the main challenge for autonomous underwater vehicle because of long delaying in its measurements (Gopalakrishnan et al., 2011). Sonar or other vision based sensors sometimes give delayed measurements due to various signal processing reasons. Time delaying estimation is made in (**?**) where neural network ~~are~~ is used to estimate the possible delay of acoustic positioning sensor for more consistent results. "ROV has no problem of delaying measurements as it has always physical wired connection. If beacon will be present above the surface of water for AUV then long delaying measurements of global sensor can be overcome but there is need to eliminate abrupt noise added value and is need to only consider reliable value of acoustic system".

Makes no sense, rewrite with clarity to make your argument comprehensive!

In a very recent methods for underwater multisensory fusion and localization Chame (Chame et al., 2018) proposed principle of contextual anticipation in which with every coming reliable sensor value the anticipation span resets to overcome abrupt noise. This anticipation span can neglect the unexpected noise of global positioning sensor but there is still massive noise of inertial sensors or dead reckoning. As we fuse data of global and inertial sensors so collective noise appear as result.

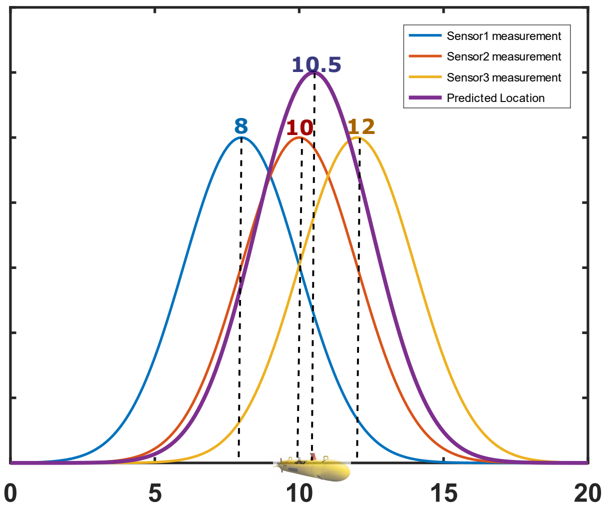


Figure 1: height of peak is showing the reconstructed results of all sensor

1.2 Our Approach

Considering the problems in literature review we proposed an autoencoder neural network technique to accurately fuse sensory data by achieving decent accuracy. Our algorithm is able to combine global and inertial information whether it is taken from acoustic positioning system, visual systems or any other source. The neural network we proposed is named as PC/BC-DIM in which input is encoded and reconstructed to eliminate massive of noise. For global sensors we are considering change and for inertial sensor we use sum of previous values as input for network. Our defined ranges automatically does not consider if a abrupt value of acoustic sensor comes as well as it reduces noises of inertial sensors due to underwater environment. The weights of presented neural network are intuitively set according to sensory data. Figure 1 is showing a one dimensional location of underwater vehicle where sensors are giving different values. Our reconstructed output is showing the predicted location. We can set the deviation of each sensor according to its reliability and massive of noise is reduced because of standardized values of network instead of abrupt noise of individual sensor. If an unexpected value or non gaussian noise will come then network will automatically ignore it because it will be outside the span of the area of weights.

Remaining paper is divided into four sections. Section 2 is about autoencoder network, we used, which briefly describe its structure, functions and capabilities. Section 3 is about results and section 4 is about discussion. In last section conclusion is presented.

2 Methodology

2.1 PC/BC-DIM Neural Network

PCBC-DIM is a hierarchical neural network in which predictive codingHuang and Rao (2011) is made compatible with Biased CompetitionSpratling (2008) and that is implemented using Divisive Input ModulationSpratling et al. (2009). Error neuron, prediction neuron and reconstruction neuron populations are the basic blocks of this network. Network has several features but we used it for cue integration and function approximation. By integration we can fuse the data of same or different sensors according to its accuracy while in approximation instead of using noisy values network returns standardized or less noisy values.

Main purpose is to setup the weights which are made up from the respective sensory inputs but equally distributed. Size of weights(W) is nxm while V is normalized transpose of W. reconstruction(r), error(e) and input(x) have equal size of mx1 while prediction neurons have size of nx1. The length of n has smaller size than m which indicates that each coming input is compressed and reconstructed. A specific range is selected for distribution of gaussian weights with equidistant shifting of each gaussian. Error is calculated on the basis of division with reconstructed output. This error is multiplied with weights and previous prediction is updated. Prediction neurons are multiplied with normalised transpose of weights and reconstruction neurons are calculated to find new error. Iteration is completed and best possible approximation of location is achieved. ϵ is a small value which is used to avoid division by zero.

$$r = V * y \tag{1}$$

$$e = x \oslash (\epsilon 2 + r) W * e \quad (2)$$

$$y = (\epsilon 1 + y) \otimes W * e \quad (3)$$

in above equations $\otimes$ and $\oslash$ is used for point to point multiplication and division, respectively.

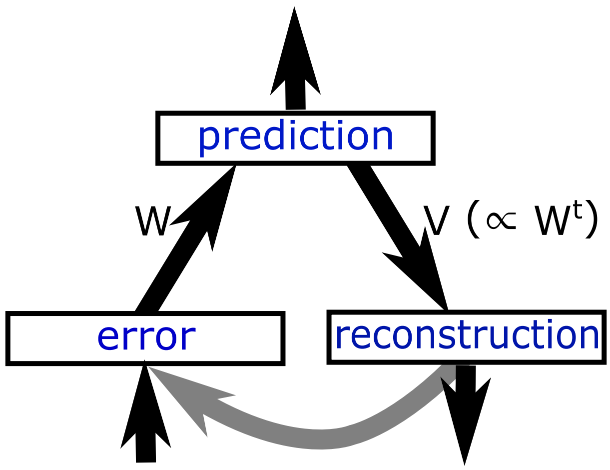


Figure 2: rectangular boxes Represents Error(e), Prediction(y) and Reconstruction(r) neuron populations. Every coming input processes from network to reconstruct the sensory data.

To localize robot we used two inertial(IMU,DVL) and two Global(USBL,DGPS) sensors. To Process it from network input sensory data is required to be encoded into Gaussian format. Deviation of sensory data is set according to its accuracy. Each sensor has size of mx1 while after combing all sensory data The size will set of input will be 4mx1. Amplitude and deviation of each sensor's encoded input is same as weights of respective input although we can change it according to need. USBL is global sensor which can be a big value so we took the difference values instead of absolute values for global sensors. To overcome residual error we took the change of USBL sensor with last location when USBL value came. Inertial or dead reckoning sensors return current change so we processed sum of current plus last values from network until USBL or other global sensory value comes. For this task there was no need for training the weights of network. We set the weights for each sensor intuitively by distribution of equidistant gaussians in respective range of sensor.

2.2 Algorithm

Write algorithm inside a box.

W $\Leftarrow$ [WI WG]
[n,m] $\Leftarrow$ $size$(W)
y $\Leftarrow$ $zeros$(1,n)
$Mval_G \Leftarrow reference$
$Mval_I \Leftarrow 0$
while $val \neq FinalValueOfSensor$ **do**
    if val_I is present **then**
        $Mval_I$+=val_I
        $xInertial \Leftarrow Gaussian(Mval_I)$
    else
        $xInetial$ $\Leftarrow$zeros(:,m/size(sensors))
    end if
    if val_G is present **then**
        $xGlobal \Leftarrow Gaussian(val_G - Mval_G)$
    else
        val_G $\Leftarrow$zeros(:,m/size(sensor))
    end if
    x = [xInertial xGlobal]

$r = ActivationPCBC(x, W)$
location = decode(r)
if sum(xGlobal)!= 0 **then**
$Mval_G = location$
$Mval_I = 0;$
end if
end while

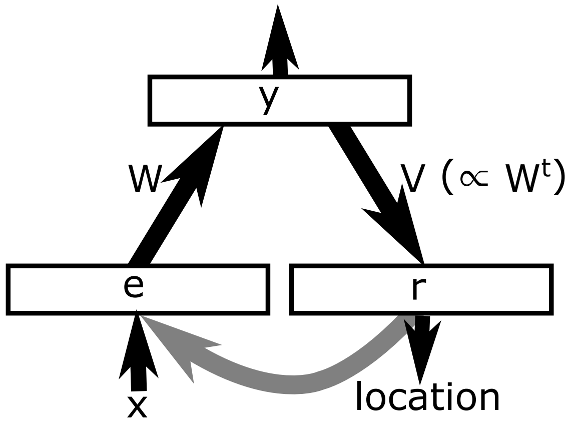


Figure 3: Impl

Algorithm for the sensor is explained.

The encoding of sensory information is missing in the methodology section.

3 Results

Write what experimental setup (*e.g.*, constants, ranges *etc.*) you used to perform each of following experiments. After this interpret your results.

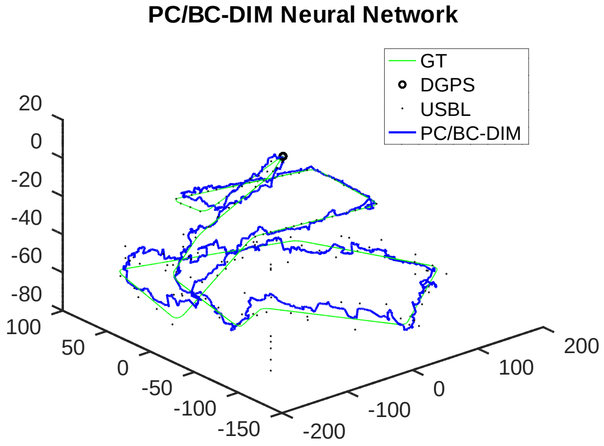
For now it may not possible to localize hundred percent exact location but our results outperformed the previous work. To show results we compared our results with Chame et al. (2018) and we observed that using PCBC-DIM neural network we achieved massive accuracy using same sensory data as they used. Other than it we did not use altimeter sensor to set a threshold for two behaviour because our method works both above and below the surface of water using same parameters. Figure 3 is indicating the visual comparison of both filters. Figure 3 and table are obtained from same iterations although we reduce iterations just to show that our filter can give more better accuracy in lesser time. If iterations are set as 50 or more in code you can see that a significant improve in accuracy. Sigma of Sensory data plays very important role. one wrongly selected sigma can give poor results for location.

Other than it, while experiments we observed that if we rely only on IMU sensor still over mean square error is smaller. Statistical comparison gives more clear differences. Table one shows the differences

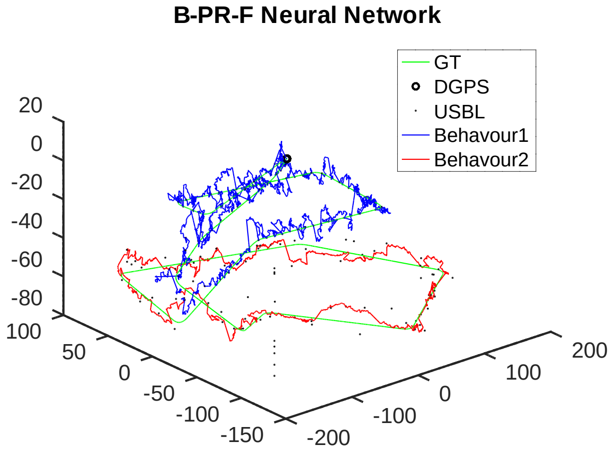
Filter	Mean Sq Error	std Error	RMS error	Time of execution(s)	Filter time
P-PR-F	51.078	2.0788	6.8385	15.612	0.00237
PC/BC-DIM	15.013	1.7864	3.439	12.900	0.00080

Table 1: Statistical comparison of techniques with ground truth

Figure 4 gives clear understanding of RMS and Std error



(a) PC/BC-DIM



(b) B-PR-F.

Figure 4: Comparison of PC/BC-DIM and B-PR-F using same data in Octave. (a) . (b) .

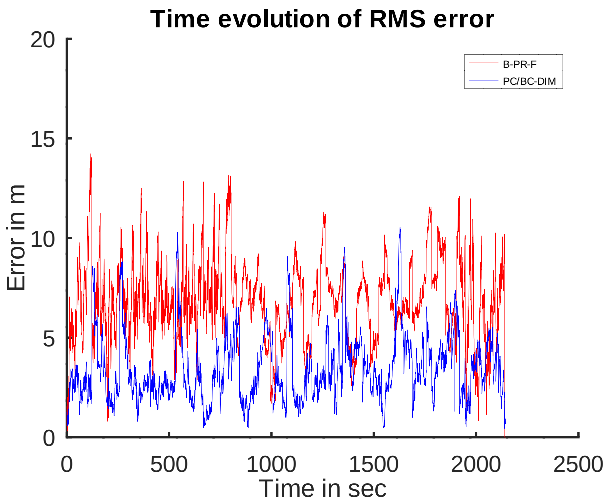
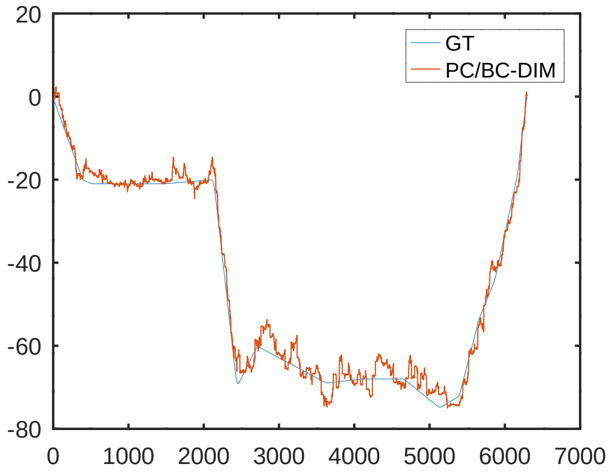


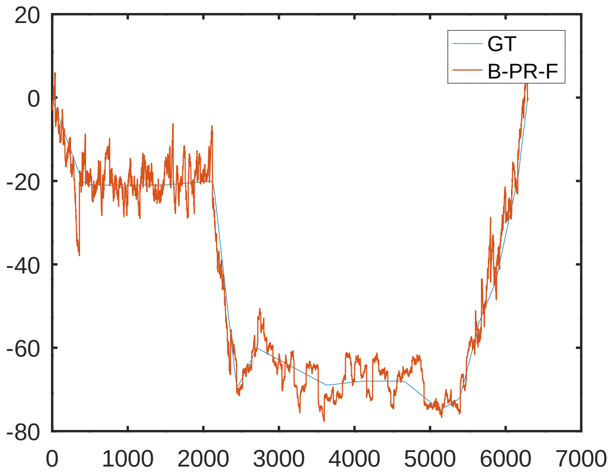
Figure 5: Comparison of PC/BC-DIM and B-PR-F using same data in Octave

4 Discussion

Conventional methods are not smart enough to deal with dynamic nature of water. Modeling of environment and hard mathematical rules make such techniques more complex. Neural Networks are very popular to deal with nonlinear systems and there is no need to mathematically model the systems for modeling the noise. Like in



(a)



(b)

Figure 6: Z axis of both filters while PC/BC-DIM has iterations of 10 to show the main difference. (a) . (b) .

Kalman filter we model noise separately but if environment is dynamic Kalman filter performs poorly because it gives noisy results. For underwater research main objective is tracking and exploring because earth is covered mostly with water. One way is to place fixed known landmarks on different places below the water to localize something. Placing fixed landmark may appear not a very good approach because it shall produce more delay in global position because vehicle will detect the location only on availability of landmark. Another way is to have multiple wireless sensor network which stays on connected with robot to inform current location which can be cost expensive. Multiple methods are proposed for wireless sensor network within water but the need is to localize the vehicle without any local support like GPS works allover the globe or at-least we have minimum dependency because GPS does not work below the surface of water. Ultrashort baseline(USBL) is a useful sensor for underwater localization and where the availability of GPS signals is not possible but sometimes delaying produces abrupt results. Fuzzy logic and multiple other protocols are proposed for wireless sensor network but again they are cost expensive and complex systems. If a ship in middle of sea wants to collect the data from the deep ocean it can send a underwater robot which can collect the data but its own location is mandatory to describe the location of the discovery. On these bases we can compare our results with a very recent technique which is named as B-PR-F neural network which outperformed previous techniques in accuracy and cost. We have successfully achieved more accuracy with more efficiency. Other than it as the input comes and reconstruct so by increasing iterations we can achieve more accuracy as Z axis of both B-PR-F and PC/BC-DIM is expressed in figure 5. It is clear to see that PCBC-DIM is fusing the sensory data as well as it is reconstructing individual sensory input to reduce noise.

5 Conclusion

Water covers more than 70 percent of earth crust which shows there is a green area for searchers to discover and explore underwater resources. To localize something below the surface of water it is essential to locate the position of robot with which reference we can estimate the location of object. GPS and other radio signals do not work below the surface of water. Acoustic positioning sensors are better choice to locate the vehicle below the surface of water. Underwater sea environment is highly non linear and unstructured so there is need to deal with this environment using neural network because they are very modern methods to model nonlinearities. We proposed PC/BC-DIM neural network for localizing the vehicle below the surface of water. To compare results we used a very recent technique which was used to localize the vehicle below the surface of water. In Experiments we observed that we achieved more accuracy in lesser time. If we increase iterations we can achieve more accuracy with a little increase in time but still our results are optimum enough. We did not used original value of any sensor because it can be noisy that was the main reason we reconstructed the input of every individual sensor and we fused the data of every sensor using same Neural Network. After experiments we came to the conclusion that PC/BC-DIM is not only giving more accuracy but it is also doing this more efficiently.

References

Al-Rawi, M., Galdran, A., Elmgren, F., Rodriguez, J., Bastos, J., and Pinto, M. (2017). Landmark detection from sidescan sonar images. In *2017 IEEE Jordan Conference on Applied Electrical Engineering and Computing Technologies (AEECT)*, pages 1–6. IEEE.

Azuma, R. and Bishop, G. (1994). Improving static and dynamic registration in an optical see-through hmd. In *Proceedings of the 21st annual conference on Computer graphics and interactive techniques*, pages 197–204. ACM.

Chame, H. F., Dos Santos, M. M., and da Costa Botelho, S. S. (2018). Neural network for black-box fusion of underwater robot localization under unmodeled noise. *Robotics and Autonomous Systems*, 110:57–72.

Corke, P., Detweiler, C., Dunbabin, M., Hamilton, M., Rus, D., and Vasilescu, I. (2007). Experiments with underwater robot localization and tracking. In *Proceedings 2007 IEEE International Conference on Robotics and Automation*, pages 4556–4561. IEEE.

Fang, S., Wang, Z., and Fan, J. (2019). Integrating sins sensors with odometer measurements for land vehicle navigation system. *Journal of Applied Science and Engineering*, 22(2):273287.

Folkesson, J., Leederkerken, J., Williams, R., Patrikalakis, A., and Leonard, J. (2008). A feature based navigation system for an autonomous underwater robot. In *Field and Service Robotics*, pages 105–114. Springer.

Fox, D., Burgard, W., Dellaert, F., and Thrun, S. (1999). Monte carlo localization: Efficient position estimation for mobile robots. *AAAI/IAAI*, 1999(343-349):2–2.

Gopalakrishnan, A., Kaisare, N. S., and Narasimhan, S. (2011). Incorporating delayed and infrequent measurements in extended kalman filter based nonlinear state estimation. *Journal of Process Control*, 21(1):119–129.

Grøtli, E. I., Tjønnås, J., Azpiazu, J., Transeth, A. A., and Ludvigsen, M. (2016). Towards more autonomous rov operations: Scalable and modular localization with experiment data. *IFAC-PapersOnLine*, 49(23):173–180.

Huang, Y. and Rao, R. P. (2011). Predictive coding. *Wiley Interdisciplinary Reviews: Cognitive Science*, 2(5):580–593.

Keatmanee, C., Baber, J., and Bakhtyar, M. (2013). Simple example of applying extended kalman filter. In *1st International Electrical Engineering Congress, Chiangmai city, Thailand*.

Khan, R. R., Taher, T., and Hover, F. S. (2010). Accurate geo-referencing method for auvs for oceanographic sampling. In *OCEANS 2010 MTS/IEEE SEATTLE*, pages 1–5. IEEE.

Leonard, J. J. and Bahr, A. (2016). Autonomous underwater vehicle navigation. In *Springer Handbook of Ocean Engineering*, pages 341–358. Springer.

Li, H., He, Y., Cheng, X., Zhu, H., and Sun, L. (2015). Security and privacy in localization for underwater sensor networks. *IEEE Communications Magazine*, 53(11):56–62.

Miller, A., Miller, B., and Miller, G. (2018). Auv navigation with seabed acoustic sensing. In *2018 Australian & New Zealand Control Conference (ANZCC)*, pages 166–171. IEEE.

Pan, X. and Wu, Y. (2016). Underwater doppler navigation with self-calibration. *The Journal of Navigation*, 69(2):295–312.

Paull, L., Saeedi, S., Seto, M., and Li, H. (2013). Auv navigation and localization: A review. *IEEE Journal of Oceanic Engineering*, 39(1):131–149.

Spratling, M. W. (2008). Predictive coding as a model of biased competition in visual attention. *Vision research*, 48(12):1391–1408.

Spratling, M. W., De Meyer, K., and Kompass, R. (2009). Unsupervised learning of overlapping image components using divisive input modulation. *Computational intelligence and neuroscience*, 2009.