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ACKNOWLEDGEMENT

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(Umair Ali)

DEDICATION

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(Umair Ali)

DECLARATION

I Umair Ali S/O Muhammad Sajjad Haider, roll # 18016522-008, MS Electrical Engineering scholar, Department of Electrical Engineering, Faculty of Engineering & Technology, University of Gujrat, Pakistan, hereby solemnly declare that this thesis titled "XYZ" is based on genuine work, and has not yet been submitted or published elsewhere. I Furthermore, I shall not use this thesis for obtaining any other degree from this university or any other institution.

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It is certified that xyz, roll # 18064422-000, MS Electrical Engineering scholar, Department of Electrical Engineering, Faculty of Engineering & Technology, University of Gujrat, Pakistan, worked under my supervision and the above stated declaration is true to the best of my knowledge.

Dr. Wasif Muhammad
Assistant Professor, Department of Electrical Engineering
University of Gujrat, Punjab, Pakistan.
Email: @uog.edu.pk
Dated:

THESIS COMPLETION CERTIFICATE

It is certified that this thesis titled “title” submitted by Name S/O Fathername, roll # 18000000-000, M.Sc Electrical Engineering scholar, Department of Electrical Engineering, Faculty of Engineering & Technology, University of Gujrat, Pakistan, is evaluated and acceptance for the award of the degree”Master of Science (M.Sc)” in Electrical Engineering by following members of the Thesis/ Dissection Viva Voce Examination Committee.

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Name of External:
Designation:
Office Address:
Email

____

Dr. Muhammad Wasif
Assistant Professor, Department of Electrical Engineering
University of Gujrat, Punjab, Pakistan.
Email: syed.wasif@uog.edu.pk
Dated:

____

Dr.Shahid Iqbal
HOD, Department of Electrical Engineering
University of Gujrat, Punjab, Pakistan.
Email: si@uog.edu.pk

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ABSTRACT

Water covers more than 70 percent of the earth and most of the underwater area has not yet discovered. For underwater exploration and unusual activity inspection, Unmanned underwater vehicles (UAVs) are used which have lesser cost and no life risks as compared to manned underwater vehicles. The known position is mandatory to make underwater exploration data meaningful. Underwater position localization is a challenging research topic because of the dynamic and unstructured nature of the seabed environment. Global positioning system (GPS) and other radio positioning systems e.g., cellular networks and Wi-Fi positioning system (WPS) are not suitable for underwater location estimation. Acoustic positioning systems are a better alternative for underwater localization but sound travelling speed is slower than electromagnetic signals. The sensors which can estimate the position in an absolute frame of reference in the underwater environment e.g., visual positioning systems and acoustic positioning systems have slower position update rate. For the sake of reliability dead-reckoning sensors like Doppler velocity log (DVL) and inertial measurement unit (IMU) are added and by fusing these sensor modalities the location of the underwater vehicle is located with more accuracy. In the case of fusion of multiple sensors, Kalman filter can not deal with non-Gaussian noise while parametric filter like monte Carlo localization (MCL) has a high computational cost. The particle filter is great for dealing highly non-linear systems but because of expensive computation cost, they are suitable for post-processing. An optimal fusion policy with the low computational cost is an important research question for underwater robot localization. We proposed PC-BC/DIM neural network which has the capability to fuse and approximate sensory information in an optimal way. Results have shown that our proposed filter has only 1.7853 standard deviation error, 3.439 root mean square error, 0.8 milliseconds of filter processing time with 12.9 seconds of total execution time against 6301 IMU, 6301 DVL and 158 USBL noise added measurements of a three-dimensional underwater trajectory.

Keywords: underwater location, PC/BC-DIM , Multisensory Fusion

CHAPTER-1

1 INTRODUCTION

Pakistan has nearly 1000 kilometre long coast from Sir Creek to Jiwani and acording to Law of sea the coastal countries are allowed up to 200 nautical miles of economic control from its territorial sea baseline. Apart from that Pakistan holds an additional 150 nautical miles of an exclusive economic zone in the deep sea. This vast coastal area comes up with numerous advantages e.g., economic strength from seafood, opportunities to explore underwater resources. Besides these benefits, there are also challenges for the Pakistan navy to monitor suspicious activities of significant sea area. All these challenges encourage researchers to play their role for the sake of economic growth and defence of the country.

Autonomous underwater vehicle (AUV) and remotely operated vehicle (ROV) are most commonly used for underwater operations. ROV is guided vehicle and is applied particularly for sea inspection, maintenance and repairing purposes (Grøtli, Tjønnås, Azpiazu, Transeth, & Ludvigsen, 2016). AUV is an unguided vessel and practices for general purposes like research, defence and exploration without interference or semi-interference from external guidance (Miller, Miller, & Miller, 2018). Self-localization of AUV is required while performing search operations e.g., in looking for missing ships, sank ships, discovering new species and natural resources. Collection of exploration data is meaningless if an AUV can not determine its exact location (H. Li, He, Cheng, Zhu, & Sun, 2015). Self-localization plays an important role in the control and monitoring of an underwater robot as well as search and rescue operations.

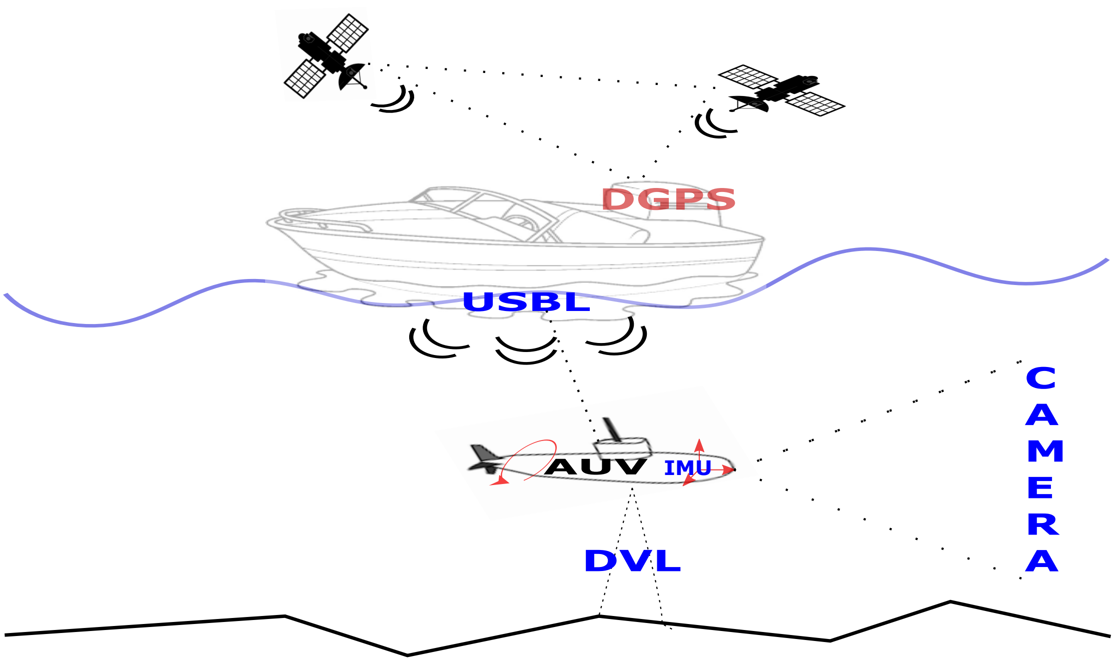


Figure 1: A general concept for localization is present in which boat have GPS connection through satellites and a beacon for connectivity with AUV. AUV contains camera, IMU and DVL sensor on it.

Underwater localization of a robot is unalike the localization in the normal territorial environment because of rapid attenuation of noise due to the dynamic and unstructured nature of salty seawater (Paull, Saeedi, Seto, & Li, 2013). Consistent location is estimated with the help of some global and differential position measuring sensors. Global positioning system (GPS) is most commonly used for self-location discovering while some force and orientation measuring sensors are combined for speed estimation and heading correction, respectively. One major limitation for underwater localization is the unavailability of GPS (Leonard & Bahr, 2016) and other electromagnetic signal-based positioning systems e.g., cellular networks and Wi-Fi positioning system etc. Salty conductive nature of the sea is highly impure for penetration of high-frequency radio signals. Similarly, with the increase in the depth pressure on inertial sensor produces abrupt and noisy results.

Sound waves are low frequency or high wavelength signals which can effectively penetrate through the seabed water. Most of the underwater communication is done on the basis of acoustic waves that is why acoustic positioning systems are used for localization in an underwater environment. An acoustic positioning system (e.g., ultrashort baseline, long-baseline, short baseline) results in absolute position measurement in the local environment (Rigby, Pizarro, & Williams, 2006). The connectivity of the acoustic system is shown in **figure 1** which is between an AUV transceiver and Ship transponder. Although, sound travelling speed is slower as compared to radio signals but accuracy is not compromised. Delay in the acoustic positioning system can be managed with the support of acoustic velocity sensor which works on the principle of the Doppler effect. Doppler velocity logs (DVL) sensor is an application of the Doppler effect in which the position of an agent is estimated with back-scattering acoustic waves using a dead-reckoning technique where the initial reference of the global position is required for such sensor. There is also a network of acoustic sensors, named as Wireless Sensor Network (WSN), for which multiple algorithms are proposed to localize a robot (Tan, Diamant, Seah, & Waldmeyer, 2011).

In a spatial reference system, egocentric and allocentric techniques are used for underwater robot localization. Using the egocentric approach, the location of an agent is used as reference for localization of other objects which can be further used for localization of secondary objects using allocentric localization methods (Al-Rawi et al., 2017). Visual positioning system provides an accurate self-location in absolute frame of reference but with lagging efficiency due to the recognition of objects. Laser-based positioning systems with the aid of some inertial sensor have been used for location estimation in a limited sea area and in shallow water.

Each individual sensor for underwater localization has some limitations e.g., acoustic positioning systems measure the position of an agent with some delay due to the limitation of sound travelling speed and visual positioning systems are dependent on the recognition of predefined objects. Inertial sensors measure change more abruptly with the depth of water and in inverse proportion, the accuracy of velocity measuring acoustic sensors also vary with depth as they need underwater land for back-scattering of sound waves (Medagoda, Williams, Pizarro, & Jakuba, 2011). Due to the limitation of each sensor multisensory data fusion appears as very complex and nontrivial task and it is required to estimate the optimal location of the robot which ensures redundancy resolution and better location estimation as compared to single sensor (Rigby et al., 2006). **Figure 1.2** is showing a general idea of multisensory fusion for optimal location in which different inputs are combined together and a fusion algorithm extracts useful features through it. Position, size, identity and distance are some examples of features which can be extracted with the help of a fusion algorithm using raw input data. Specifically in an unknown underwater environment, where there are no fixed landmarks or predefined maps to recognize the objects and to estimate the self location of underwater robot, the acoustic positioning systems are better alternative than vision-based positioning systems. In conclusion, absolute positioning technologies (e.g., visual or acoustic positioning systems) and dead-reckoning technique based technologies (inertial, velocity measuring sensors) are combined to locate an underwater robot.

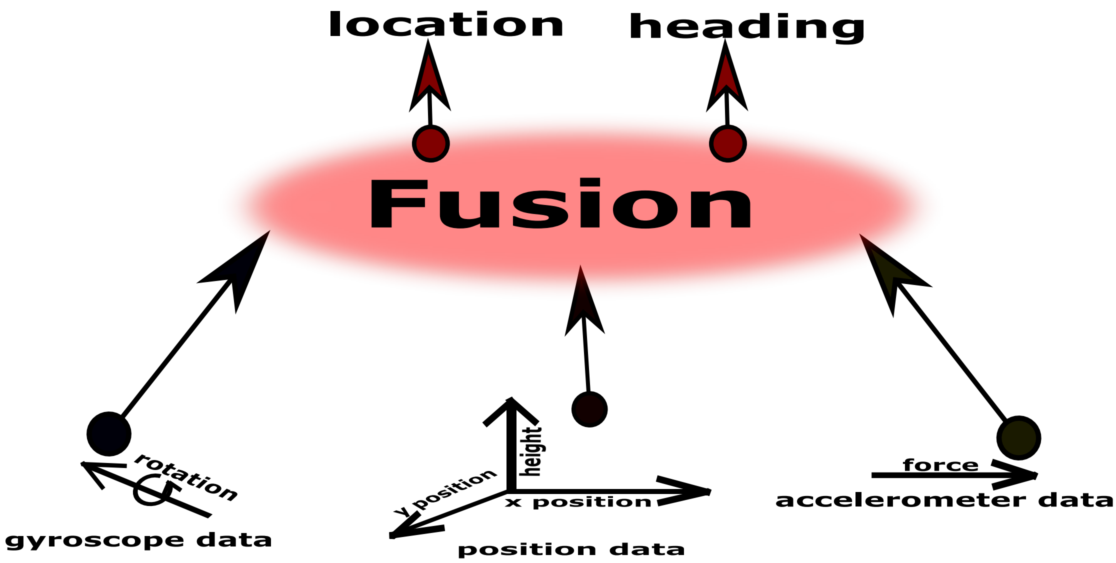


Figure 2: General idea of multisensory fusion in which three different sensors are fused to give optimal pose

1.1 Problem Statement

Collection of exploration data in an unknown environment is meaningless when there is no known frame of reference. In the middle of the ocean, there is always ambiguity for location estimation. Radio waves can not travel through salty water of the sea due to its conductive nature and high density. Acoustic positioning systems are the better alternative for underwater position estimation in an absolute frame of reference but results are produced with delayed measurements because of the non-linear behaviour of sound in water. Similarly, vision-based positioning systems need some known objects to refer but noise impurity of water also matters. For underwater self-localization of a robot, every available sensor has limitations. Multisensory fusion is needed for redundancy resolution and optimal location estimation instead of a single sensor for localization in underwater environment. Conventional fusion policies such as Kalman filter can not model highly non-linear noise of the underwater environment. Multimodal hypothesis based techniques such as Monte-Carlo localization have high computational cost even in the presence of reliable sensory data. Optimal fusion policy for an underwater robot localization is required for dynamic and unstructured nature of the seabed environment.

1.2 Objectives and Scope of Study

The objectives of the thesis are:

- To investigate available technologies and techniques of underwater localization.
- To examine state estimators and their limitations for underwater multisensory fusion.
- To analyze recent developments for underwater localization
- To develop an efficient and accurate fusion policy for optimal location estimation in dynamic and unstructured underwater environment

CHAPTER-2

2 Literature Review

In this chapter, from a very basic to advance level review is presented. Autonomous Underwater vehicles (AUV) are now converting from prototype to real working robots for scientific exploration and military operations (MahmoudZadeh, Powers, & Zadeh, 2019). Available technologies and fusion algorithms with their specifications are discussed below

2.1 Navigation Systems for Underwater Localization

Navigation systems are divided into three main categories (inertial, acoustic and geo-positioning systems) for underwater vehicle localization. In literature, these technologies have been used in various projects.

2.1.1 Inertial or Dead-reckoning

Most of AUVs are working on dead reckoning principle in which current change is integrated to past states for prediction of position. For underwater localization, the internal or inertial sensory information is used for prediction of location using motion estimation (Ko, Kim, & Noh, 2011). The inertial sensor incorporates error with time and produces inaccurate results especially in-depth. Inertial measurement unit (IMU) is a sensor which is widely used for motion estimation. IMU contains a triaxial accelerometer, triaxial gyroscope and electrical compass for linear, angular and heading, respectively (J. Zhang, Wang, Xie, & Shi, 2014). Motion estimation below the surface of the water is not similar to the territorial environment. The underwater environment is highly nonlinear for motion estimation. Inertial sensors contain unstructured noise of water which can be overcome by the modelling of the sensor (Karras & Kyriakopoulos, 2007). Modelling of underwater sea environment is highly difficult that is why position prediction from motion sensors become a crucial task. The problems which can be faced by state estimator algorithms are reviewed in the later section of fusion algorithms.

Another dead reckoning sensor is DVL which is sometimes used in parallel with IMU sensor(Lee, Hong, & Seong, 2003). DVL sensor works on the doppler principle and the velocity is estimated. DVL is more accurate in shallow water and with depth, its accuracy improves. Acoustic signal is triggered and after backscattering the velocity of the vehicle is estimated (Dukan & Sørensen, 2013) (Hegrenæs, Ramstad, Pedersen, & Velasco, 2016) (Karimi, Bozorg, & Khayatian, 2013). In underwater, DVL is more accurate than accelerometer and its accuracy grows with depth. An accelerometer is comparatively accurate near the surface of the water and DVL is the most time accurate in deep water. DVL is an expensive sensor due to which it is not used for common projects. DVL works on acoustic waves due to which it can face variation in time of arrival. DVL is used with other auxiliary sensors to predicted the underwater location in various projects. A typical working of DVL sensor is explained in figure 3 by (Vasilijevic, Borovic, & Vukic, 2012)

In an underwater environment, inertial sensors are used in both ROV and AUV but the main purpose is always motion estimation and for aid, some other sensors are also integrated with it. In (Aras, Shahrieel, Ab Azis, & Othman, 2012) for building a low-cost ROV, IMU is

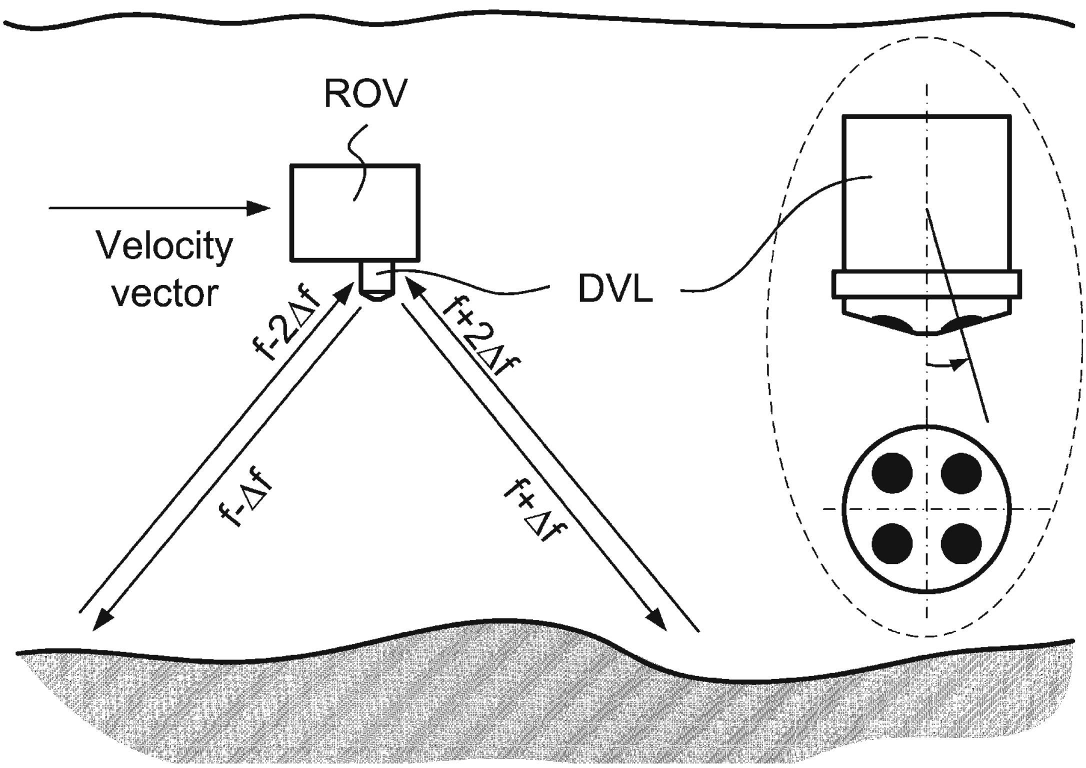


Figure 3: DVL general working and shape is presented by (Vasilijevic et al., 2012)

combined with pressure sensor and compass and this integrated sensor is tested through National Instrument DAQ for 4 degrees of freedom (DOF) in underwater. IMU is comprised of IDG500 (gyro) and ADXL335 (accelerometer) chip for linear and angular movement estimation. As the reliability of IMU varies with the pressure that is the main reason for adding a pressure sensor and heading is corrected through the magnetic-resistive compass. In (J. Zhang et al., 2014) IMU is used for 3D location estimation of a robotic fish when the sampling rate is used as 50 Hz. The accelerometer of IMU is used as odometry but the noise of gravity involved so to the integration of past states was not a wise method. DVL can not be affected by gravity and pressure so acoustic sensors are the better choice for deep underwater odometry or velocity estimation.

In literature, IMU and DVL are integrated by various researcher considering the underwater dynamics of the sea. In (Dukan & Sørensen, 2013) DVL is integrated with other sensors using an integration filter. A DVL has 3 DOF and a 600KHz DVL, with 7Hz ping rate, used by Dukan covers the range of 0.7m to 90m with a standard deviation of 0.3cm/s at 1m/c. Similarly, a new generation DVL is used by (Hegrenæs et al., 2016) which is mounted in the lower part of AUV and has 500 KHz rate with 180m range, 0.2% deviation at 0.1 cm/s.

2.1.2 Acoustic Positioning Systems

Over time, Dead reckoning based sensors accumulate the residual error and this does not remove until correction or external sensor is added. GPS doesn't work below the surface of the water an alternative is acoustic positioning systems. There are three types of acoustic positioning systems

- Long baseline (LBL)

- Short baseline (SBL)
- Ultra-short baseline (USBL)

Figure 4 is showing the geometry and working principle of acoustic sensors. In literature, all of these sensors have used for various purposes. Long baseline acoustic positioning systems use 3 or 4 transponders for estimation of Underwater position and are very accurate relative to the other two. When there is a system of dead reckoning sensors, such as IMU and DVL, then LBL is used as correction sensor with the help of some fusion algorithms (T. Zhang, Chen, & Li, 2016). LBL is an acoustic sensor and underwater sound travelling is considered as non-linear system (Lawrence, 1985) which indicate that LBL itself has multiple challenges.

SBL is comparatively expensive system and need more beacons for underwater communication while USBL is used as stand-alone position estimationing system. LBL is mostly used for underwater sensor networks and USBL has shorter ranges. Due to slower travelling speed, acoustic positioning systems have different time of arrival (TOA) consider TOA choosing a USBL in a locally unknown environment is better choice. The propagation delay affects the accuracy of the vehicle by addition of non-gaussian noise in USBL as well.

(Caiti et al., 2014) proposed mixed LBL and USBL system for underwater location estimation. In the experiment, LBL is used as fixed nodes with the help of moored modems while a USBL is placed on the Typhoon AUV. IMU has 10Hz rate and it not expensive as DVL that is why IMU is used when Acoustic data is not present. LBL is fixed acoustic nodes which makes underwater sensor network. Multiple Protocols are presented for underwater sensor network and various algorithms are presented for that. The review and challenges are presented in (Heidemann, Stojanovic, & Zorzi, 2012) for an underwater sensor network.

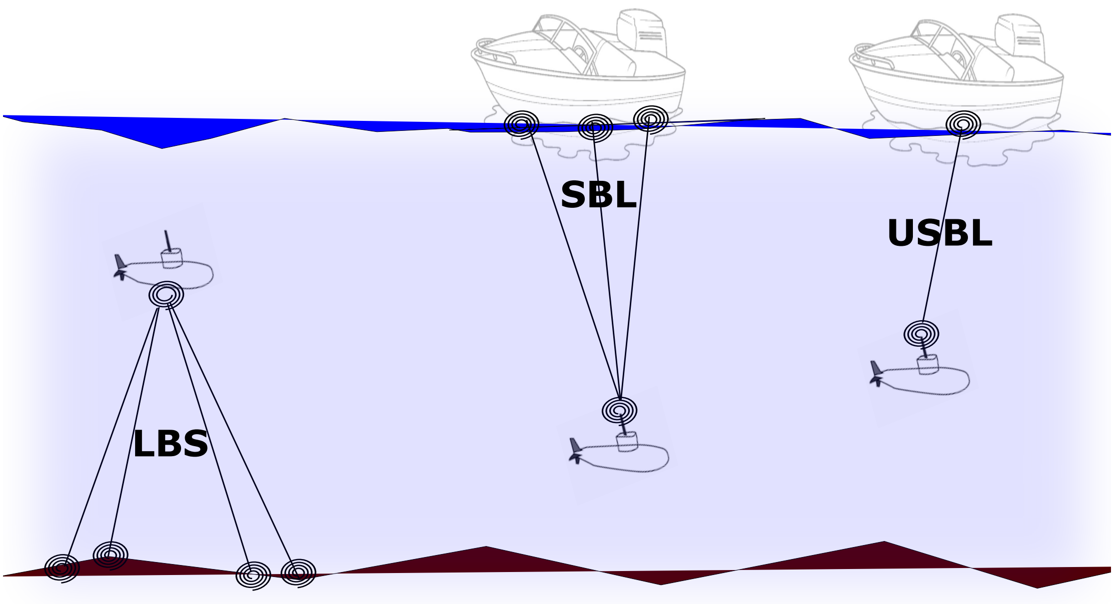


Figure 4: acoustic sensors and their geometry is presented which shows LBL are fixed nodes, SBL uses on-board multiple transponders and USBL needs single transponder to estimate underwater location

Acoustic systems have a limitation of high delays of arrival, dependency on the environment and low data rates. Sometimes abrupt noise also tempers the useful data so magnetic induction is another technique which is being considered for underwater communication (Akyildiz, Wang, & Sun, 2015). It has comparatively higher data rates but the range is lower than acoustic position systems in an underwater environment. Magnetic induction technique is not mature enough and is not directly applicable due to directional communication and salty conductive nature of seawater temper conductivity.

2.1.3 Geophysical based localization systems

In vision-based localization, the very first task is the recognition of the objects. In some recent advancements regarding underwater localization, the researchers have proposed various useful techniques considering the dynamics of an underwater environment. A visual odometry algorithm is developed for underwater robot localization (Álvarez-Tuñón, Rodríguez, Jardón, & Balaguer, 2018) 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. Different colours and intensity differentiate images and region of interest is selected by segmentation (Chen, Zhang, Dai, Bu, & Wang, 2017). Acoustic systems are considered as expensive sensors and contain non-linear noise. Monocular vision system containing a single camera is a better alternative than other positioning systems in a known environment for underwater localization. Camera estimates location with the delay of recognition and it is also dependent on known objects for reference. Low cast pressure sensor and IMU are integrated with a camera to make a Monocular Odometry for underwater vehicles (Creuze, 2017) for pose estimation. Similarly, (Ferrera, Moras, Trouvé-Peloux, & Creuze, 2019) proposed visual odometry algorithm which is tested on different images with incrementing the noise.

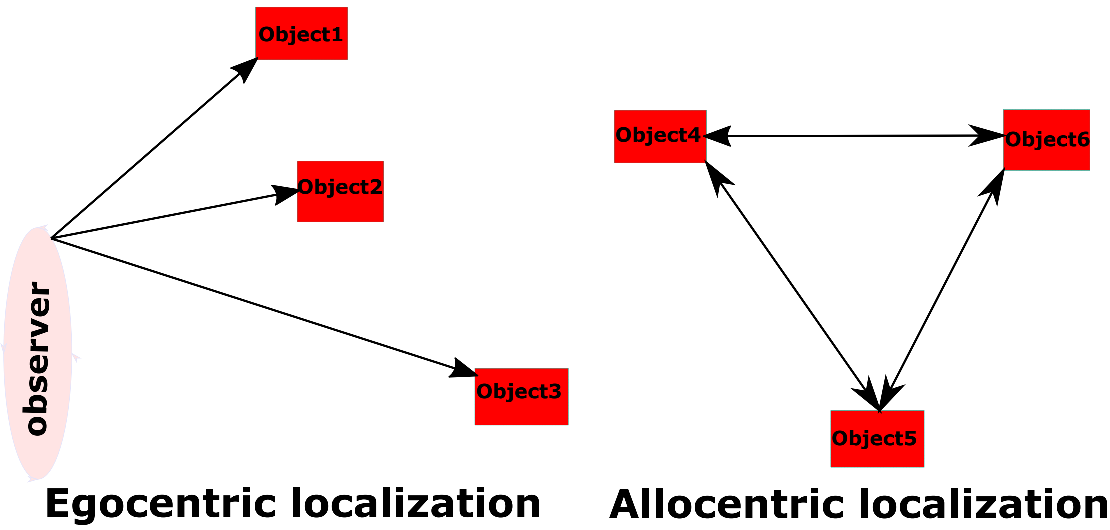


Figure 5: Visual localization approaches

Figure 5 shows egocentric and allocentric localization concept but the visual camera faces difficulty in object recognition due to impure water. Imaging and ranging sonar are a better option in such environments. Robot location is estimated online using imaging sonar which gives better results than dead reckoning using DVL and gyroscope (Johannsson, Kaess, Englot, Hover, & Leonard, 2010). For a partially structured underwater environment (e.g., dams, port) EKF is used to extract the line features and AUV is localized with the help of 360-degree sonar (Ribas, Ridao, Neira, & Tardos, 2006). Like a camera, there are limitations for sonar-based localization systems. Sonar-based algorithm of self-localization of AUV is presented in (Petrich, Brown, Pentzer, & Sustersic, 2018) which is a robust technique.

The magnetic compass is another geo-referred device and in underwater localization, it is also a part of IMU and the main purpose of a compass is correcting the heading using the Geomagnetic field.

2.2 Fusion Algorithms for Underwater Localization

For underwater localization using multi-sensor fusion (MSF) various methods are discussed (Pan & Wu, 2016) (Tan et al., 2011) (Leonard & Bahr, 2016) (Paull et al., 2013).

2.2.1 Kalman Filter

Kalman Filter is a stochastic filtering based state estimating algorithm that comprises prediction and estimation stages. Figure 6 is showing the general working of the Kalman filter in which filter gives the hypothesis of location by combining prediction hypothesis of filter and measurements of sensory data. In (Karras & Kyriakopoulos, 2007) Kalman Filter is used to fuse inertial and visual positioning sensory information for an approximation of location from a fixed earth reference but results can not satisfactory for deep water. A chronological linear state estimator performs poorly in presence of non-linear motion equations of the underwater environment.

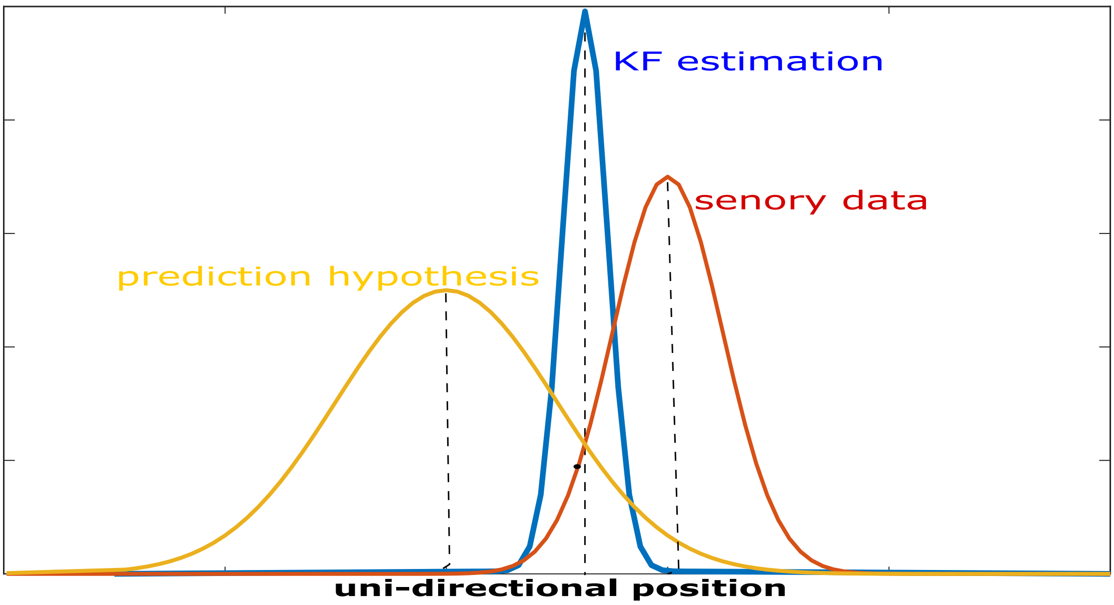


Figure 6: General working principle of Kalman Filter

As the above figure 6 is showing kalman filter does prediction with the help of designed model. Underwater environment can not be modeled using linear concepts due to which prediction hypothesis can not be accurate and there will be no overlapping of output of kalman filter.

2.2.2 Extended Kalman filter

Extended Kalman filter (EKF) is used for converting the non-linear system to locally linear by involving Taylor series expansion and it is based on ”minimum mean square error” estimation principle. A general configuration of the EKF is presented in figure 7. To produce a single state vector of underwater location from various sensory information, Extended Kalman filtering methods are investigated in (Ranjan, Nherakkol, & Navelkar, 2010). To somehow EKF can model some non-linear models but it increases computational cost. As seawater is highly dynamic in nature so EKF also has limitations in underwater location estimation e.g., for underwater environment noise covariance matrix is difficult to obtain and a constant covariance matrix can not be used for dynamic scenarios. An adaptive EKF is proposed for dynamic covariance matrices in (Shao, He, Guo, & Yan, 2016) considering prior limitations. Similarly, using online maximization estimation approach, a new adaptive EKF is presented to update noise and prediction covariance matrices for underwater vehicle localization (Huang, Zhang, Xu, Wu, & Chambers, 2017). EKF is a locally-linear model and follows Gaussian distributions.

Ground speed, heading, altitude and depth is integrated using EKF by (Ribas, Ridao, Cufí, & El-fakdi, 2003). EKF algorithm is implemented on GARBI ROV and main sensor DVL is used. A typical system of underwater localization using an extended Kalman filter is described in the figure below

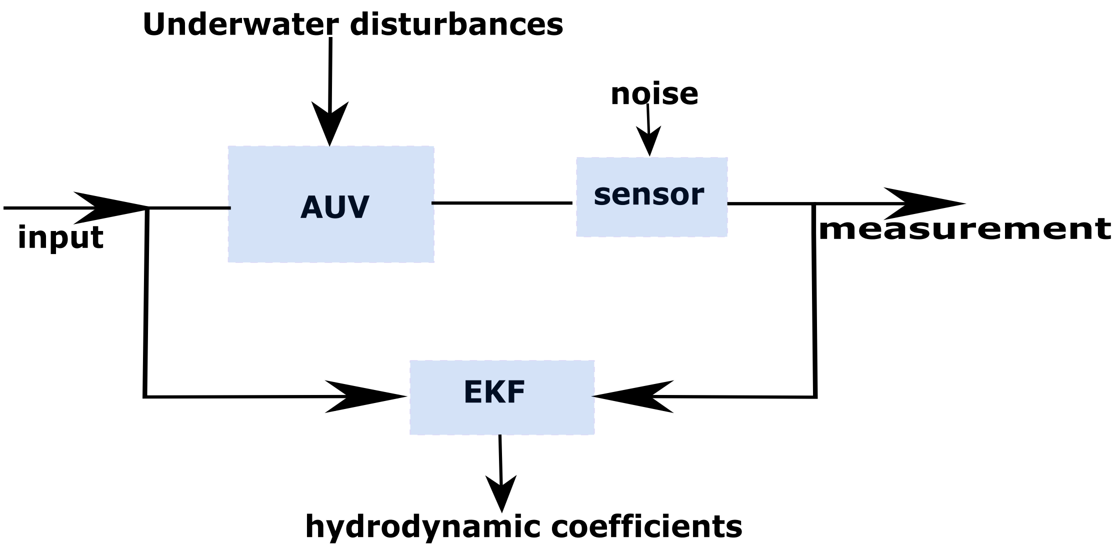


Figure 7: Typical EKF scheme

(Karimi et al., 2013) has simulated for underwater localization in Matlab in which main sensor IMU and auxiliary sensor DVL are used for motion estimation. Considering non-linearity of underwater environment EKF and UKF are compared on NPS AUV. Process noise and measurement noise are added to make the process similar to the real-time environment. EKF performed more accurately using the same sensory data. The main reason for the limitation of Unscented Kalman filter (UKF) is double integration of accelerometer data and due to which sigma points goes through integration to produce a new distribution of model output in every step. (Tal, Klein, & Katz, 2017) has integrated the accelerometer and gyroscope data into an inertial system which is further corrected by auxiliary sensors to feed to an EKF. EKF accurately able to find the next state and simulated environment showed that Technion Autonomous underwater vehicle (TAUV) performed better with EKF state estimator.

2.2.3 Unscented Kalman filter

Unscented Kalman filter (UKF) is better approximation than EKF because it consider true deviation points and transformed through weighted sample mean and covariance (Wan & Van Der Merwe, 2000) (Sabet, Sarhadi, & Zarini, 2014) (Allotta et al., 2016). UKF has been used for vision-based systems as well as for other sensory information fusion. A UKF in (Lebastard et al., 2010) is used to recognize the sphere with which reference the location of a vehicle is estimated. With the depth of the sea, the performance of each sensor varies so (Ko, Noh, & Choi, 2014) proposed simultaneous estimation of the pose of vehicle and depth of sea using UKF but terrain should be known. Although commonly UKF converges accurately, but in case of high variance EKF is a better choice than UKF (Rhudy, Gu, & Napolitano, 2013) and accuracy of UKF improves by increasing sigma points. UKF is a non-linear model and follows gaussian distributions so it has relatively higher computational cost than EKF. Figure 8 is showing the convergence of UKF and EKF which briefly describe the convergence attitude of EKF and UKF. Accuracy of UKF is better than EKF but with more sigma points the computational cost of UKF increases.

To achieve the best possible accuracy research proposed various schemes. In (W. Li, Wang, Lu, & Wu, 2013) a novel scheme is proposed in which DVL and strap-down inertial navigation system (SINS) are deployed and for alignment adaptive UKF are used. UKF working is similar to a KF as both filters predict the mean and covariance before updating measurements. By using adaptive UKF measurement noise covariance is estimated hence to improve the performance of UKF. A navigation filter based on UKF is presented by (Allotta et al., 2015) for two Typhoon (TifOne and TifTu) AUVs. AUV offers robust behaviour against different sensor configuration. It is concluded that UKF is more accurate for underwater localization and accuracy improves in the presence of USBL.

2.2.4 Particle Filter

In literature for underwater localization, researchers have also work on non-Gaussian distribution. In specific particle filter (PF) is the non-linear model which approximates to the real system. PF has more expensive computational cost than UKF and EKF. The motion of AUV and underwater location estimation of the acoustic positioning system are highly non-linear processes and contain non-gaussian noise so (Rigby et al., 2006) used PF for the fusion of USBL and DVL sensors. Due to multiple hypothesis particle filters gives delayed results even when there is reliable sensory data but accuracy is not compromised. (Petillot et al., 2010) Presented a method of underwater localization for AUV in the structured environment. Particle filters rely on Monte Carlo approximations in which a large number of particles are distributed for achieving massive accuracy.

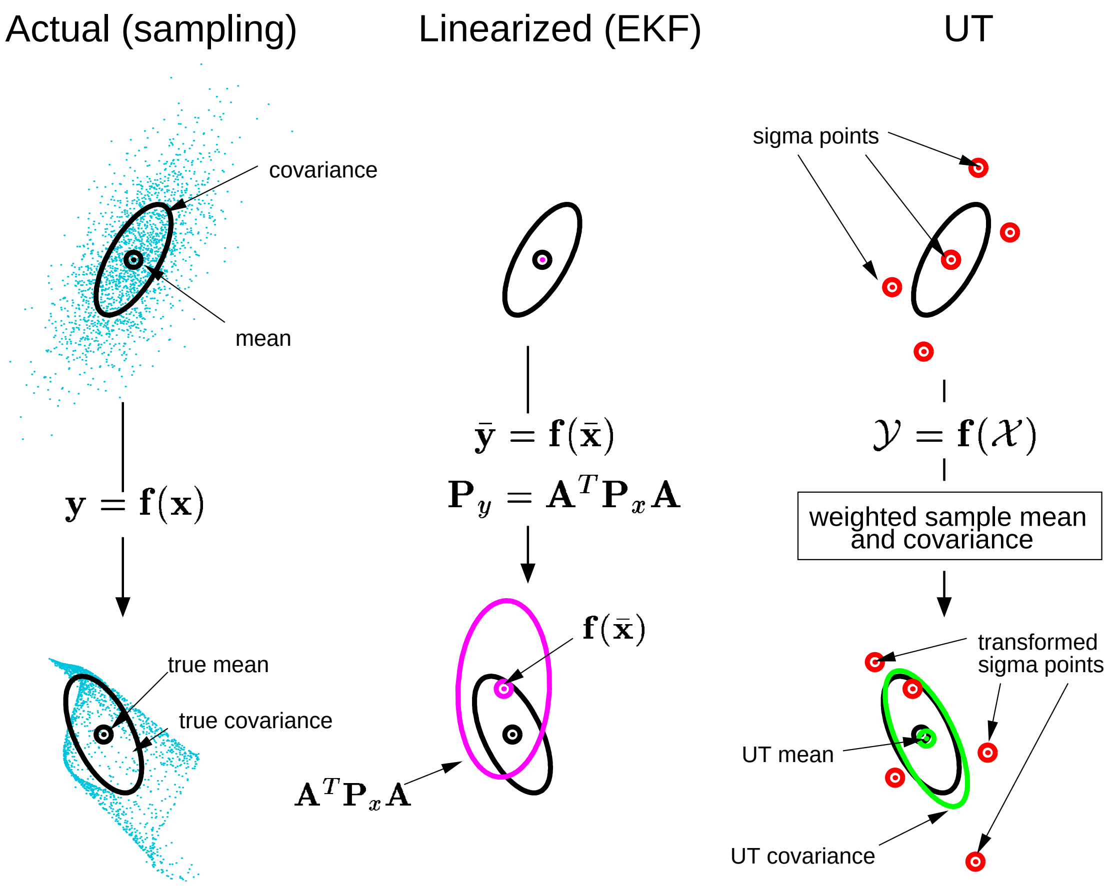


Figure 8: Comparison of Unscented transform (UT) and linearlized EKF by (Wan & Van Der Merwe, 2000)

In (Mandić, Rendulić, Mišković, & Na, 2016), OWTT-iUSBL system uses a known waveform which is triggered by beacon that is present at the known place. AUV captures the signal with the help of Tetrahedral Hydrophone array. The Particle filter is used which obtain the information from sensor data and fuse it with the motion model. It is proposed that particle filter produces more accurate trajectories for AUV. Most of the underwater simultaneous localisation and mapping (SLAM) work is done using a particle filter. Guillem (Vallicrosa & Ridao, 2018) has used particle filter for state estimation of AUV Virtual and real environment. The proposed technique is capable of running online and represent the environment more accurately.

Table is giving specifications of conventional filters for underwater localization

Filter	Working	Model	Computational cost	Distribution
KF	Unimodel	Linear model	Low	Gaussian
EKF	Tylor series	Locally linear model	Low-Medium	Gaussian
UKF	Sigma points	Non-Linear	Medium	Gaussian
PF	Multi-model	Non-Linear	High	non-Gaussian

Table 1: Comparison of conventional state estimator for underwater localization

2.2.5 Machine Learning Methods

Machine learning methods are preferred to deal with highly non-linear systems, nowadays. The main focus of the researchers for underwater localization is to use neural networks. Least squares regression formulation presented in (Dellaert & Kaess, 2006) saves the past states for posterior state estimation and is a better scheme than the Extended Kalman filter for underwater localization. Chame (Chame, Dos Santos, & da Costa Botelho, 2018) proposed principle of contextual anticipation in which, with every coming reliable measurement of global sensor, 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. Sabra (Sabra & Fung, 2017) proposed a novel underwater localization scheme called Best Suitable Localization Algorithm (BSLA). BSLA dynamically fuse multiple position estimates of sensor nodes using fuzzy decision support system of selecting a suitable algorithm.

For a single onboard vehicle one approach to overcome noise is modelling of non-linearities by supervised learning (Fang, Wang, & Fan, 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 the autonomous underwater vehicle because of long delaying in its measurements (Gopalakrishnan, Kaisare, & Narasimhan, 2011). Sonar or other vision-based sensors sometimes give delayed measurements due to various signal processing reasons. Time delaying estimation is made in (Houegnigan et al., 2017) where a neural network is used to estimate the possible delay of acoustic positioning sensor for more consistent results.

2.2.6 Bio-inspired Approaches

Some bio-inspired work is presented demonstrating the location estimation just like a fish senses the flow rate under the water and using the predefined map the location can be estimated (Muhammad, Toming, Tuhtan, Musall, & Kruusmaa, 2017). Similarly based on mammals navigation Dolphin SLAM (Silveira et al., 2015) 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.

3 Research Methodology

Location of exploration data is meaningless without a reference of known location and the underwater environment is highly nonlinear. Various methods are employed for the purpose to locate an underwater vehicle for the structural and unstructured environment but available techniques are either not able to predict underwater location accurately or have high computational cost. The main challenge for underwater localization is to predict underwater location accurately in an optimal way. A novel neural network-based technique is proposed in which weights are set intuitively. Each sensory information is encoded into a gaussian format and it is processed through the filter of equidistant weights. The proposed method not only predict individual sensory information with accuracy but it also fuses the sensory information of global and inertial sensor. The general idea of the proposed neural network is presented in figure 9. The proposed PC/BC-DIM neural network and simulations are described below

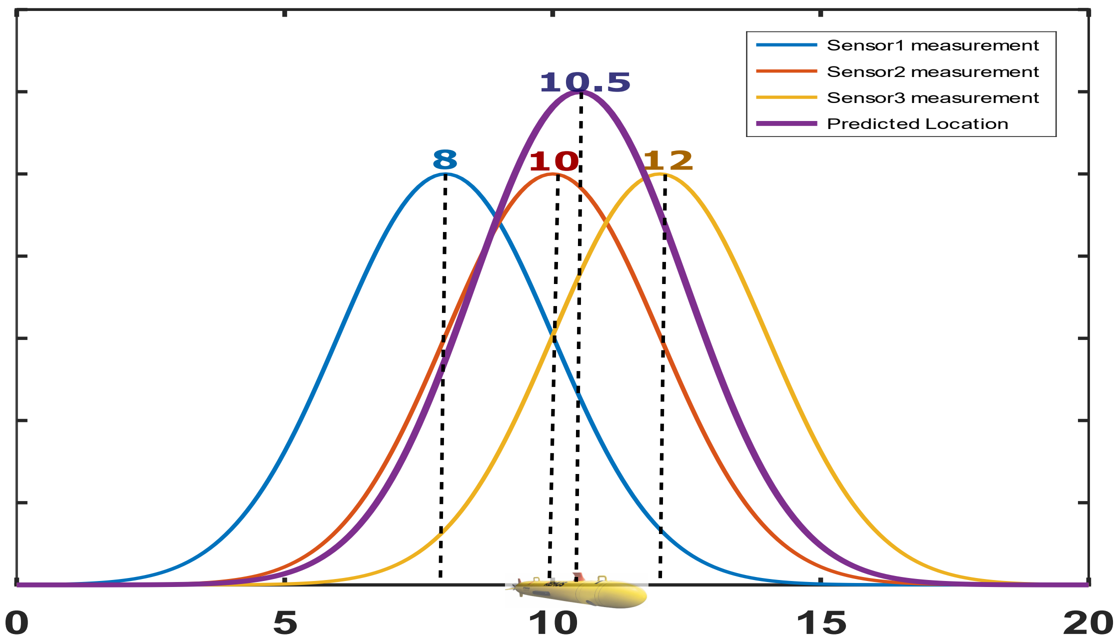


Figure 9: General working of PC/BC-DIM in which highest peak is showing the reconstructed results of all 3 sensory data is presented

3.1 PC-BC/DIM neural network

PC/BC-DIM is a hierarchical neural network in which predictive coding (PC) (Huang & Rao, 2011) is made compatible with Biased Competition (BC) (Spratling, 2008) and that is implemented using Divisive Input Modulation (DIM) (Spratling, De Meyer, & Kompass, 2009). A processing stage of the network is made up of three different neuron populations. The functioning of each neuron population is expressed in 3.1, 3.2 and 3.3 equation.

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

$$e = x \oslash (\varepsilon 2 + r) \tag{2}$$

$$y = (\varepsilon 1 + y) \otimes W * e \tag{3}$$

where x, e and r are input vector, error and reconstruction neuron activation functions respectively having the size of m by 1 for each. y is a vector of prediction neuron activations having the size of n by 1. W is a matrix of feed-forward synaptic weight values with the size of n by m and V is the normalized transpose of W. The mathematical operators $\otimes$ and $\oslash$ are used for point to point multiplication and division respectively. Value of ε_1 is 10^{-6} to prevent prediction neurons from becoming non-responsive and it also sets the baseline activity rate of prediction neurons. Value of ε_2 is 10^{-4} to prevent division by zero and determines the required minimum strength of input to effect the response of prediction neurons. Prediction neurons activation (y) are initialized with small random values or with zero values. The PC/BC-DIM network iterates for a number of iterations to determine stable response of the each neuron population activation.

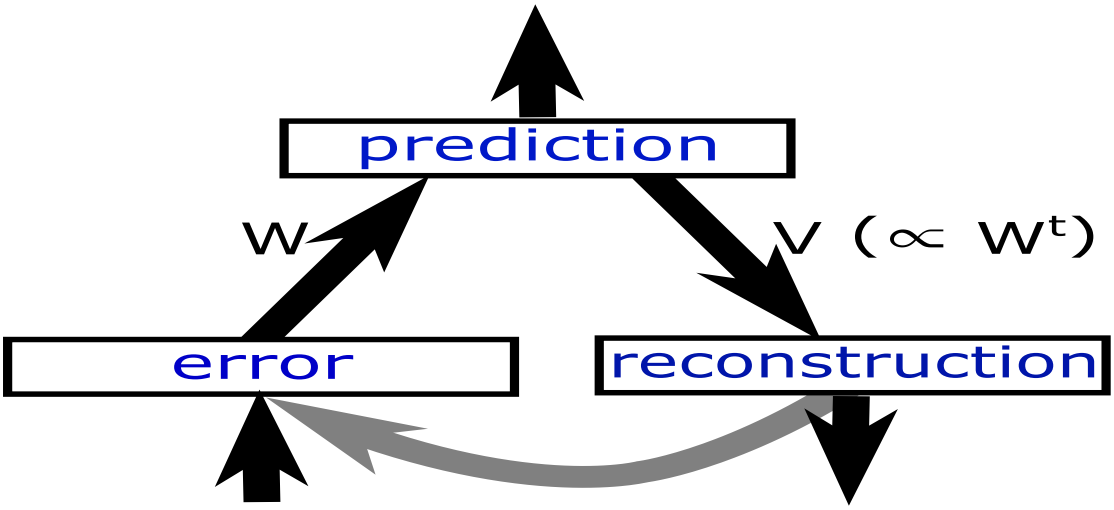


Figure 10: rectangular boxes Represents Error(e), Prediction(y) and Reconstruction(r) neuron populations. Every coming input processes from network to reconstruct the sensory data.

The input of PC/BC-DIM network is termed as causes which is encoded into useful information. Every new input play its role in training of weights. Adding up same sensor input not only increases the size of weights but it also consuming more computation and makes the network slow. To overcome this situation the proposed network can be trained on the explaining away pattern of reasoning in which the same sensor input is not required and only different information from weights is considered to update the weights. The values of y are prediction points for distinct causes and expected input is obtained under these prediction points. The difference of reconstructed input r and actual input x is represented with e. Weights W are the most important part of the network because it sets the possible range of causes. W as a whole can be assumed as a model of external environment or codebook of possible representation or input stimulus. Each row of W is like a basis vector or elementary component of the whole system. The divisional approach is considered to minimize the error in PC/BC-DIM network instead of a subtractive method as the subtractive mathod converges to solution more slowly and solution is less sparse furthermore subtractive method is less biological plausible.

PC/BC-DIM can perform computations with probability distributions when input is a probability function. Weights are the elementary components so every specific input can be reconstructed from these weights. PC/BC-DIM has the ability to reconstruct noiseless signals. The **figure 11** is showing that how a noisy cause reconstruction through PC/BC-DIM neural network.

Algorithm 1 ActivationPCBC(x,W)

for i = 1:iterations
r = V*y
e = x ./ (e_2 + r)
y=(e_1+y).*(W*e)
end

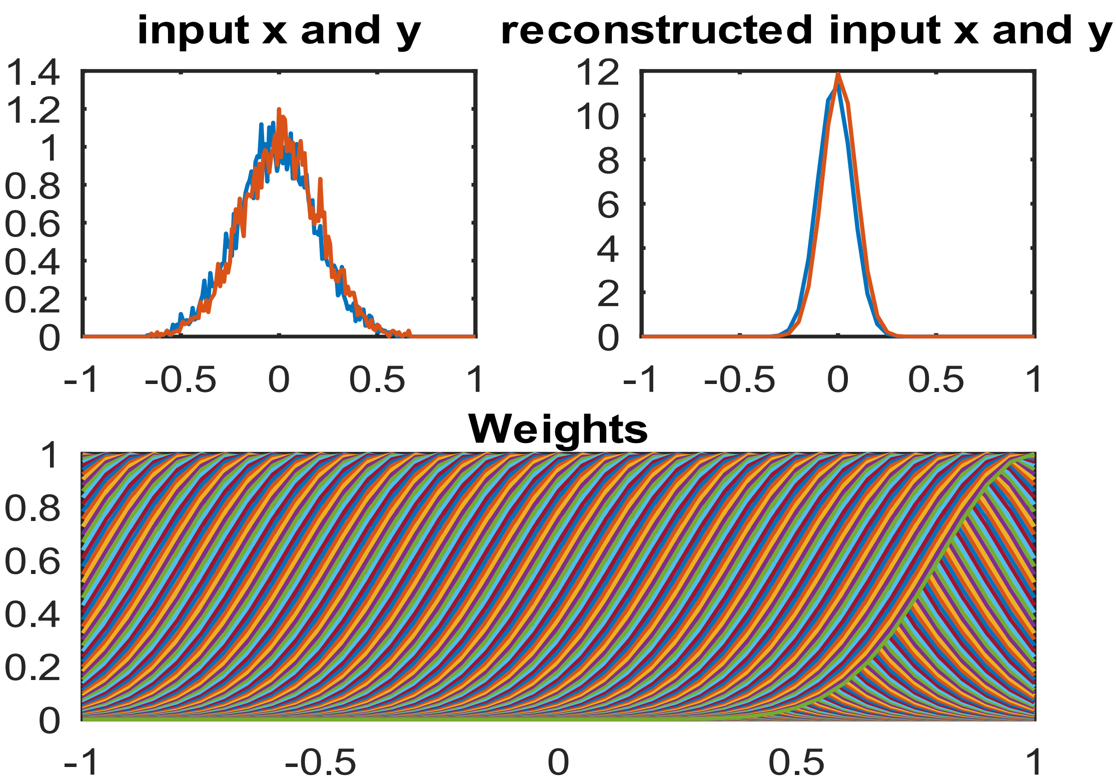


Figure 11: sensory noisy measurements (x and y) are reconstructed through PC/BC-DIM with the help of presented weights and reconstructed response (without noise) in shown

Sensory measurements of underwater robot are just discrete values of position and they are mixed with a abrupt and non-gaussian type of noises. Weights are considered as a modelled system that is why input stimulus decides the nature of weights of network. PC/BC-DIM network weights are set intuitively and less noisy reconstructed results are obtained using noisy sensory data. Input of sensors can be encoded in various formats and to encode them into probability density function one-dimensional Gaussian equation is used and presented in **equation**.

$$x = exp(\frac{(range - center)^2}{-2\sigma^2}) \tag{4}$$

A single dimensional gaussian encoded input is used to set a weight vector in W weight matrix until the training of weights completes. For a trained network encoded input is processed from the network for some number of iterations. For a medium size network 25 numbers of iterations are enough to produce a stable reconstructed input. Reconstructed input can be decoded back with the help of the **equation**.

$$\mu = \frac{\sum_i z_i s_i}{\sum_i z_i} \tag{5}$$

where μ is the mean value of probability density function (PDF) where z_i is the activation of neuron i and s_i is a receptive field (RF) of neuron i. Similarly, the variance can be calculated using the equation below

$$\sigma^2 = \frac{\sum_i z_i (s_i - \mu)^2}{\sum_i z_i} \tag{6}$$

The filter has the ability to combine likelihood of the prior to calculate the posterior probability. Fusion or integration of multiple causes is another ability of the filter.

3.1.1 Training of Weights

In a neural network, the main part is always training of weights. In PC/BC-DIM input makes the weights so weights are dictionary for all possible inputs. One way to train the weights is to store non-noisy different type of inputs in a matrix form but in simulations, weights are intuitively set for convenience to observe the performance of the network. The weights for all sensors is shown in the figure 14. In simulations, all weights are concatenated like all sensors and reconstructed input r is obtained

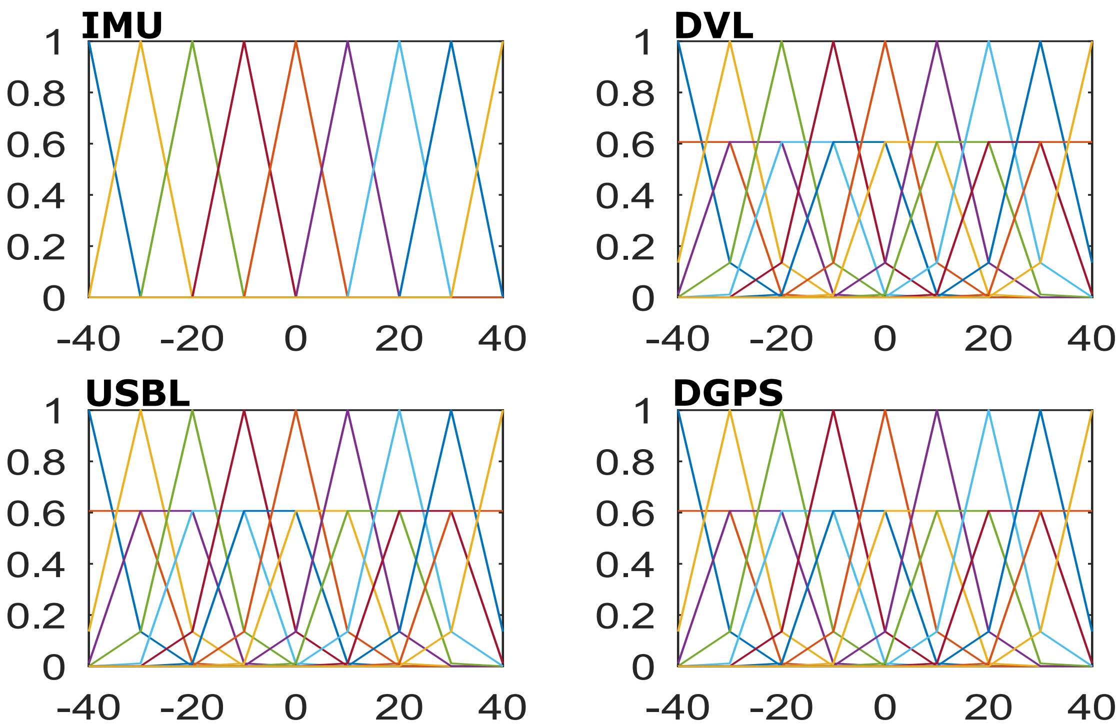


Figure 12: weights for each sensor used in experiment

3.1.2 Multisensory Data fusion using PC/BC-DIM

In real-time experiments, there are always multiple sources of information about the same sensory stimulus. This sensory information can be obtained from the same sensory modality or different sensory modalities for the same task. Purpose of multisensory fusion is to determine a single estimate for a different type of information which obtained from different sensor modalities. For example, human performance in cue integration is optimal as it can use different sensory information for the same task by considering the reliability of every cue. PC/BC-DIM has the ability to optimally integrate these sensory modalities. The figure 12 is demonstrating the integration of two sensory cues which are present at a different location. Their weights, actual input, prediction neuron and reconstructed input is mentioned

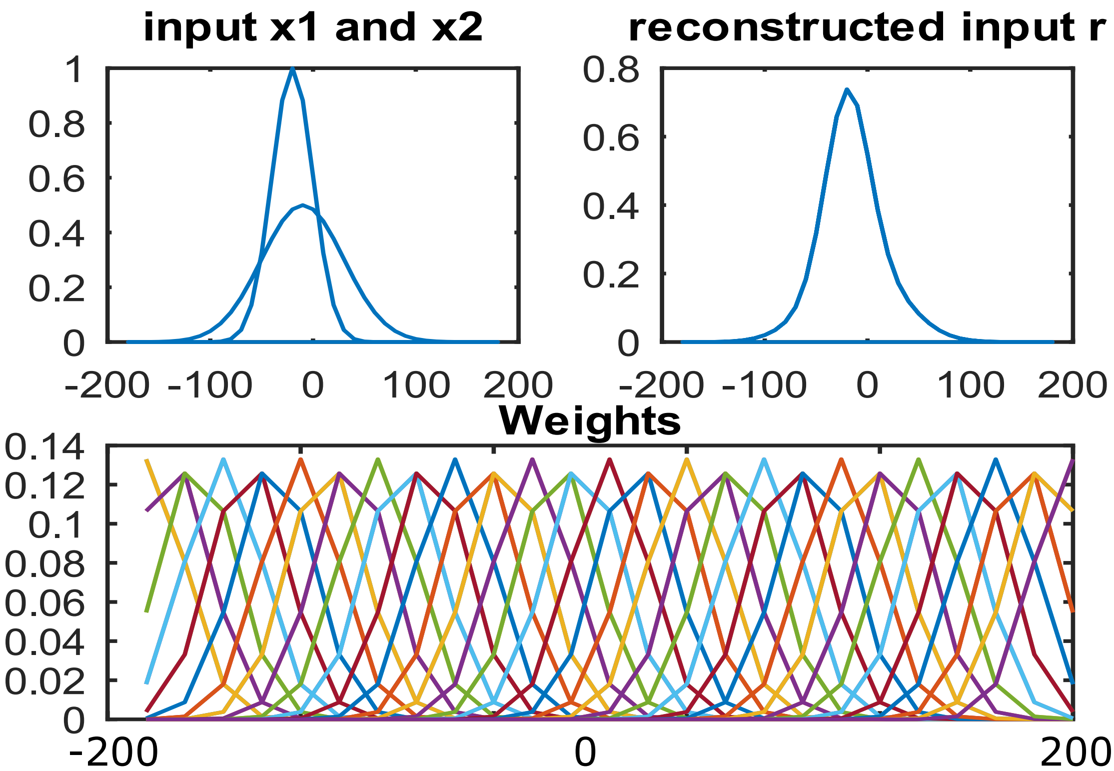


Figure 13: two different sensor x1 and x2 are fused and reconstructed single estimate is shown

3.2 Implementation for Underwater localization

To localize an underwater robot deadreckoning and absolute positioning sensors are used. Each sensory data is first encoded into the individual probability density function (PDF) and these concatenated encoded inputs are processed from PC/BC-DIM neural network to achieve a best possible single probability density function as reconstructed input r. This reconstructed input r is decoded using **equation** to find a single mean value which indicate the optimal position. For that purpose mean and variance of each sensor is required to find. The mean value is selected as the actual measurement of the sensor and variance is a possible range of that sensory value. Each encoded sensory data has the size of (m by 1) while after combing all sensors the data will be a vector of size (N times m by 1), where N indicates the number of all sensors. Amplitude and deviation of each encoded input are the same as weights of respective input.

3.2.1 Sensors for Simulations

One dimensional and same nature of information (e.g., position, heading etc) is processed from the filter at a time. In the implementation section IMU, DVL, USBL, and DGPS systems are used to estimate the location of AUV. IMU and DVL are dead-reckoning sensors that is why they have to integrate previous states to estimate the current state. USBL and DGPS result in an absolute location of an autonomous underwater vehicle.

GPS doesn't work below the surface of the water but has a fine accuracy above the surface of the water. USBL is an alternative of GPS which can work below the surface of water. Absolute location points of UAV can be located with the help of USBL but there is always delay in the time of arrival acoustic signal. Other than having low data rate the USBL also contains noise due to disturbances caused by the underwater environment. As support, some dead reckoning sensors are added in which IMU is a very well known sensor. So collectively the unavailability of a low rate positioning sensor in an underwater environment is aided with the help of IMU and DVL.

Dead-reckoning sensors specially IMU contains nonGaussian noise in underwater environment. From IMU the position of an underwater vehicle is derived by double integration of accelerometer data. IMU can not completely estimate the position of an underwater vehicle due to the presence of underwater noise. For redundancy resolution and improving accuracy, DVL sensor is added in parallel to IMU. DVL is more accurate in shallow water, but in deep water it has concerns as well because the velocity of underwater robot is estimated with the help of backscattering acoustic signals. These acoustic signals trigger from the underwater robot and after backscattering from the earth below the surface of water these signals help to estimate the velocity of AUV. To estimate position adding up previous states to current state produces a residual error which can be corrected by positioning sensor.

3.2.2 Encoding of Sensors

Every sensor has either limitation of reliability or accuracy so that each sensor is encoded with different variance and the maximum peak value of every encoded sensor is one. The figure 13 is showing the 5th value of all sensors. **Equation 4** is used for encoding each sensory input. One point to note is that exact real measurements of sensors are not directly used. The encoded input is processed from PC/BC-DIM neural network and reconstructed output will return the exact location. Each sensor is concatenated to a single vector before processing from the network. The equation of sensor encoding has three main parameters of inputs, centers and standard deviation.

$$y = A\exp(\frac{(range - c)^2}{2\sigma^2} \tag{7}$$

Range is the distribution of inputs and c is center or mean of respective input. σ is the deviation of input and A is amplitude which is set equal to 1.

3.2.3 Decoding of reconstructed input

With the help of decoding **equation** the mean values of reconstructed input is selected. PC/BC-DIM is not only reconstructed each input but it alse fuses multiple sensory data. Reconstructed

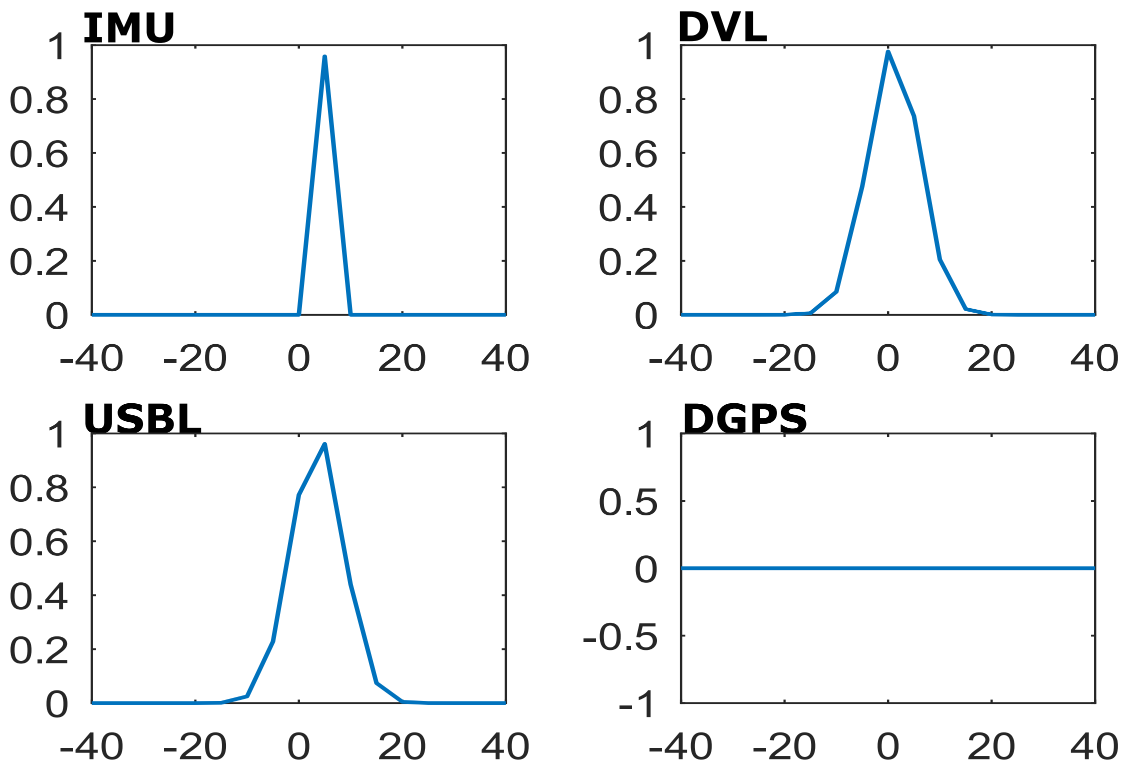


Figure 14: Encoded sensory data at a specific instant is shown during experiment

input can return diversity in results based on experience because of the deviation of each sensor and weights. If the range is selected from 0 to 40 with the difference of 10 and sigma is selected as 1 then the output will saturate on the multiple of 10s (e.g.,0,10,20,30 and 40). With the increase in variance of sensor and weights, the distribution of output will scatter. Value of reconstructed input also depends on the shape of weights. If prior information of specific type is available then reconstruction of input will be according to that likelihood.

3.3 Algorithm of PC/BC-DIM for Underwater Localization

As generally there are two types of sensory information is available. One is an inertial or dead reckoning and second is global fixes information. For global or absolute position estimation the difference of last position (during the presence of global position) from the current position is feed to the PC/BC-DIM network. Inertial sensors are integrated until global fixes correct the residual error of the dead-reckoning sensor and then these are reinitialized to zero. The algorithm is presented below for an underwater robot localization using PC/BC-DIM neural network.

WI are weights of inertial sensor and WG are weights of global sensor which are concatenated and stored in W synaptic connection weights. $Mval_G$ is input of global sensor and $Mval_I$ is inertial input. Until the last value, the filter consistently update multiple sensory inputs with a single reconstructed response r. Inertial values are integrated with previous and global value takes the difference of last value as sensory input. If there is no value present for any sensor then encoded input is assigned with zeros. x is concatenated input and r is reconstruction response. Location is determined by the decoding r response.s

Algorithm 2 PC/BC-DIM

```
W ⇐ [WI WG]
[n,m] ⇐ size(W)
y ⇐ zeros(1,n)
Mval_G ⇐ reference
Mval_I ⇐ 0
while val ≠ FinalValueOfSensor do
    if val_I is present then
        Mval_I+=val_I
        xInertial ⇐ Gaussian(Mval_I)
    else
        xInetial ⇐zeros(:,m/size(sensors))
    end if
    if val_G is present then
        xGlobal ⇐ Gaussian(val_G − Mval_G)
    else
        val_G ⇐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
```

CHAPTER-4

4 Results and Discussion

4.0.1 Source of sensory data (adjust)

Ranges for inputs is set from -40 to 40 with the difference of 5 and distribution of centres is same but with the difference of 10. IMU is a very noisy sensor it is not wise to involve every value of it that is why its deviation is 1 so it always approaches to some standardized values instead of abrupt sensory values. DVL is more accurate than IMU so its deviation or variance is set as 5 like USBL and DGPS to involved almost every value of each sensor. If at any instant when there is no data available then encoded input is assigned with zeros. DGPS is not presented in an underwater environment figure 13 is showing zeros values.

The proposed filter is designed after considering the possible noise of every sensor and the variance is assigned to encoded input. For experiment collectively IMU, DVL, USBL and DGPS are used. Simulation data is taken from (Chame et al., 2018) in which a ground truth (GT) is the actual noise-free trajectory. For IMU data double derivative of GT trajectory is taken and noise is added to it so that it diverges from reference GT trajectory by adding previous values of IMU. DVL data is a single derivative of GT with some noise so it is less noisy than IMU data. From reference GT trajectory with the equal time difference, various points are selected and in those selected point abrupt values are added. DGPS works fine above the surface of the water so similar GT values are selected for DGPS sensor.

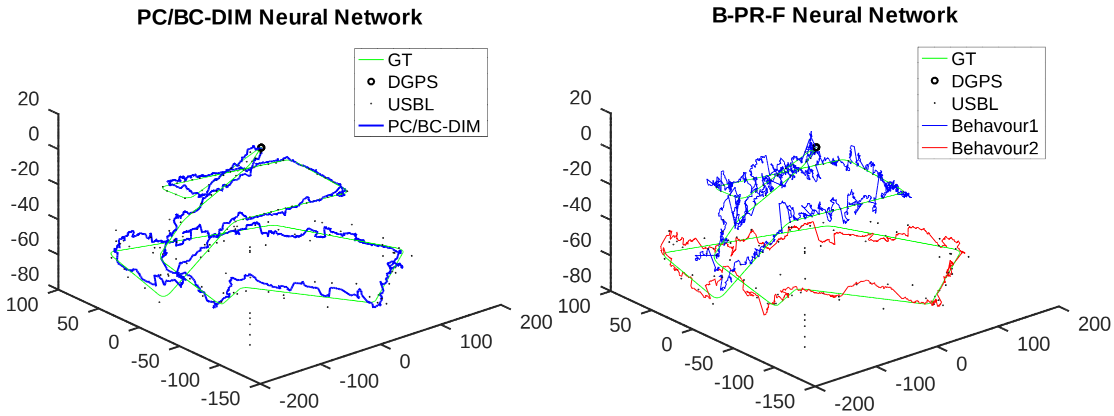
The experiment is conducted in an open-source software named as GNU Octave. To compare results, sensory data is the same which was used by (Chame et al., 2018). Sensory data of simulations include IMU, DVL, USBL, DGPS and Altimeter. Altimeter sensor is not used as a proposed filter gives optimal location without any manual switching. Ground truth data is actual trajectory while all other sensory data is derived from it. IMU data is simulated by twice the differentiating and adding noise to it so integrating the measurements diverge from the original trajectory. Similarly, DVL is one time differentiated and noise is added that is why it is relatively accurate than IMU. USBL data is obtained by selecting instances from ground truth and abrupt noise is added to some of the instances. DGPS is same as ground truth but a few values are taken. USBL has slow data rates as compared to other sensory data.

Above figure is demonstrating the visual difference between two filters using same sensory data. It is clear that PC/BC-DIM is returning more converging results. B-PR-F has two behaviour of deep and near surface while PC/BC-DIM has optimal attitude without any manual switching of any sensor. Green trajectory is showing ground truth data.

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 2: Statistical comparison of techniques with ground truth



(a) PC/BC-DIM (b) B-PR-F.

Figure 15: Comparison of PC/BC-DIM and B-PR-F using same data in Octave

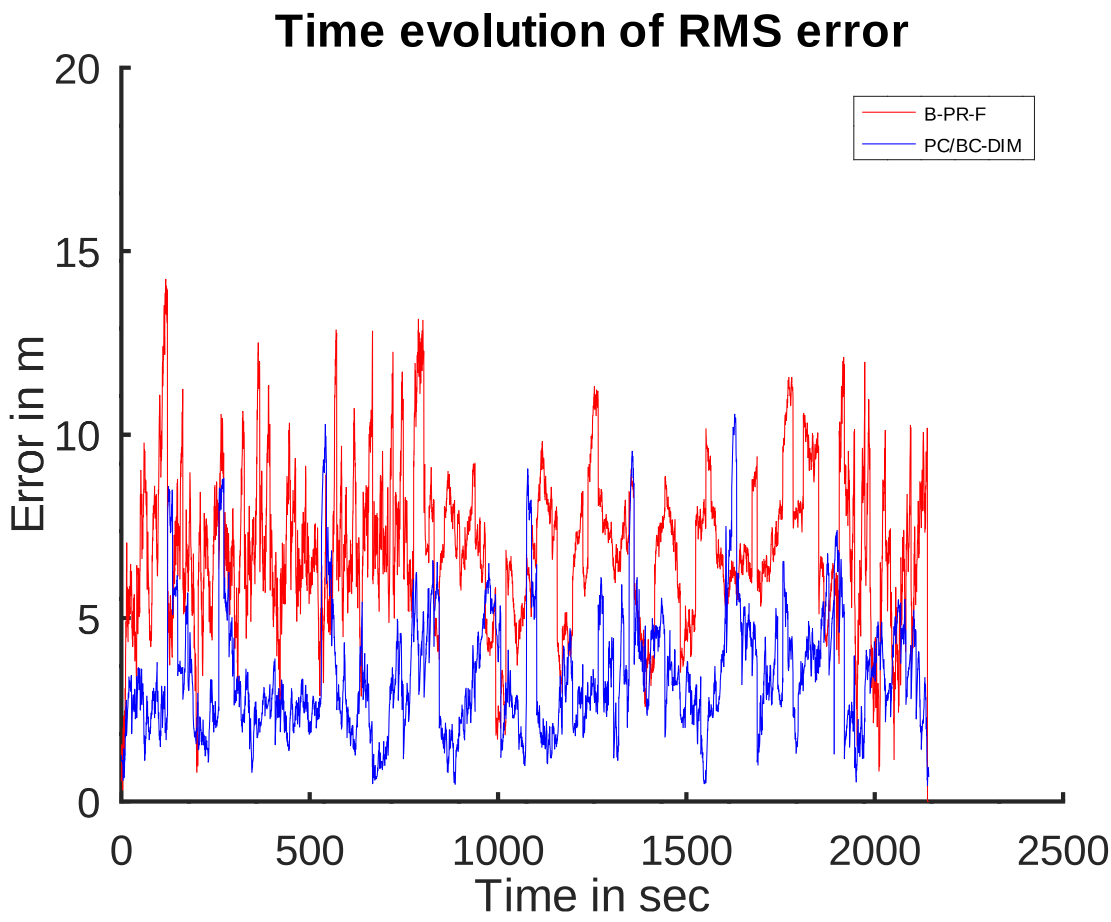
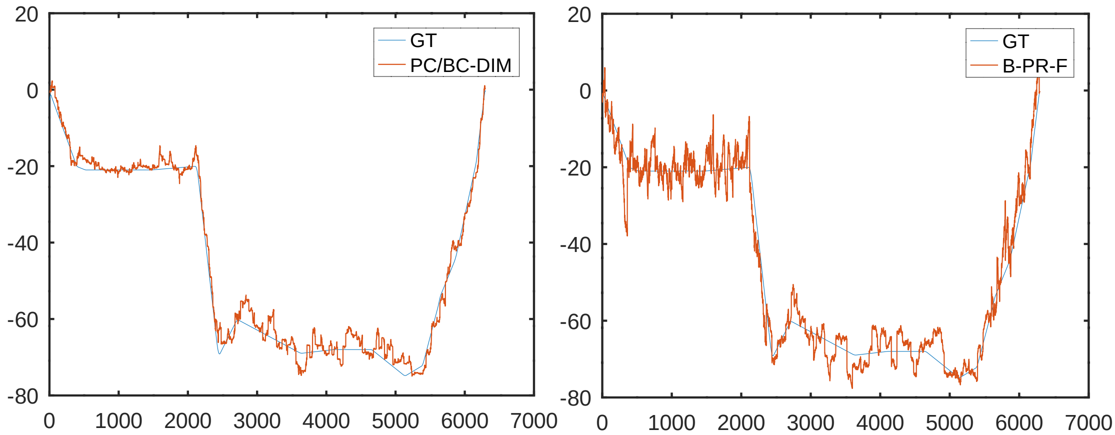


Figure 16: PC/BC-DIM and B-PR-F mean square error (RMS) with evolution of time

Figure 16 is clearly representing the difference between RMS error of both neural networks. The spikes in PC/BC-DIM can be improved further by increasing the input points of encoding but a minor computation cost will increase. For more deep visualization figure 17 is representing z-axis comparison with GT.

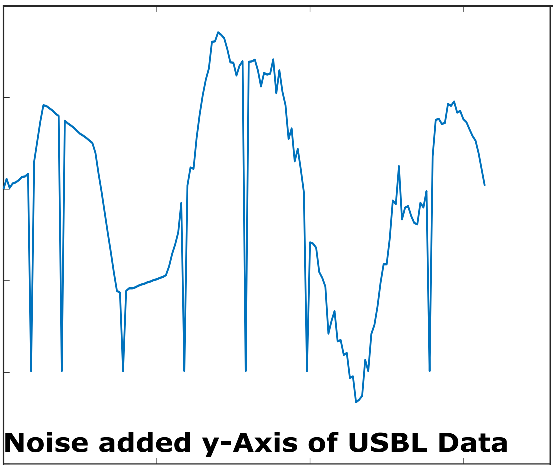
Conventional methods are not smart enough to deal with the dynamic nature of water. Mod-



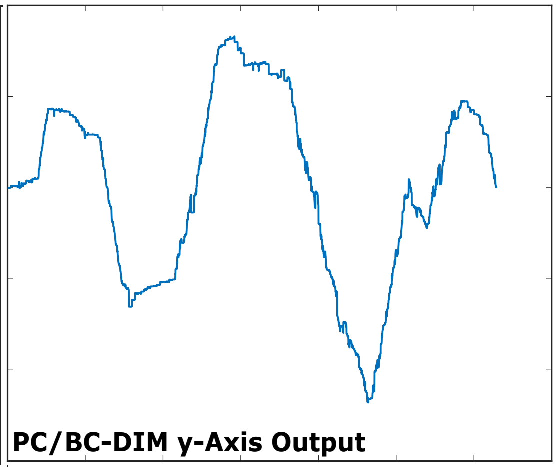
(a) PC/BC-DIM (b) B-PR-F.

Figure 17: Z axis of both filters while PC/BC-DIM has iterations of 10 to show the main difference

elling of environment and hard mathematical rules make such techniques more complex. In the Kalman filter, we model noise separately but if the environment is dynamic Kalman filter performs poorly because it gives noisy results. Extended Kalman filter can convert the non-linear system to the locally linear but still underwater environment is highly unpredictable. Particle filter can deal underwater noise by multiple hypotheses but it makes localization process slow even there is less noisy data. Least square regression is better than extended Kalman filter and it has to save prior states to estimate posterior states. For optimal fusion algorithm, Chame proposed that abrupt noise of USBL can be eliminated by relying on other sensors and reliable data can be considered. For this purpose Chame proposed principle of contextual anticipation which resets in the presence of reliable sensory data of USBL. Sabra proposed that it is better to use different techniques for different environments. Camera-based systems do not have this problem but they can produce a delay in recognition of known landmarks for self-location determining. Our proposed method has a range of equal distance weights so abrupt noise can be overcome because it will be outside the ranges. Weights can be set differently according to need but here the main focus is to eliminate abrupt noise and fusion of sensory data. Other than Abrupt noise of USBL PC/BC-DIM also reduced dead-reckoning error. 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 the Z-axis of both B-PR-F and PC/BC-DIM is expressed in figure. 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.



(a) noisy USBL



(b) PC/BC-DIM

Figure 18: noise added values of USBL and trajectory obtained from reconstructed output are shown

CHAPTER-5

5 Conclusion

Water covers more than 70 per cent 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 the water it is essential to locate the self-position of the robot. GPS and other radio signals do not work below the surface of the water. Acoustic positioning systems are a better choice to locate the vehicle in an unknown underwater environment. Low time of arrival for a global position is the main reason to add a dead reckoning sensor for positioning estimation. Dead reckoning sensors contain abrupt noise and residual error. residual error correction can be overcome by global sensor but modelling of motion estimation sensors is a difficult task as Underwater sea environment is highly non-linear and unstructured. Conventional fusion policies either have low accuracy or high computational cost. There is a need to deal with this environment using neural network because they are very modern methods to model non-linearities. PC/BC-DIM neural network is proposed for localizing the vehicle below the surface of the water. Weights are set according to the nature of sensory data and position is estimated. In Experiments, it is observed that more accuracy is achieved in lesser time as compared to a very recent method using the same sensory data. After experiments, we concluded that PC/BC-DIM is not only giving more accuracy but it is also doing this more efficiently. In future PC/BC-DIM can be used for underwater image recognition, target tracking and simultaneous localization and mapping.

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