Underwater Robot Localization Using PC/BC-DIM Autoencoder

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ABSTRACT

Underwater robot localization is challenging research topic because of 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. In case of fusion of multiple sensors Kalman filter can not deal with non Gaussian noise and other parametric filters have high computational cost as well as wireless sensor networks are expensive and complex. In this paper we proposed a novel technique to overcome the noise of Inertial Measurement Unit (IMU) and Doppler Velocity Log (DVL) and we fused this to estimate the position of vehicle when global sensory information is not available. Our technique does not only optimally fuse the data of two inertial and two global sensors but it also overcome the highly abrupt noise of Ultra-Short baseline (USBL). Simulation results show that our proposed model outperformed previous techniques for underwater robot localization.

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[1]. AUV is unguided vessel and uses for general purposes like research, defense and exploration without interference or semi-interference from external guidance[2]. Looking for missing planes or drowned ships and discovering of new species or natural resources are required to locate. Collection of exploration data is meaningless if we can not describe the exact location of vehicle[3]. Navigation plays important role to control a underwater robot where it works as a feedback for correcting heading and location of underwater robot.

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[4]. A big problem for below water navigation is unavailability of GPS radio signals[5] because territorial communication is done using electromagnetic signals which does not work below the surface of water. We can go for alternatives like acoustic and vision positioning systems[6]. Vision based systems are needed some defined locations like some signs and landmarks to localize[7] otherwise there is no global location. Considering this acoustic position systems are more better choice for underwater localization[8] specially for unknown environment where there are no fixed landmarks. Acoustic positioning sensors can have higher frequency but still it contains 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 Pan[9] the problem of residual error will remain there that is main reason to have a global sensor. Optimal fusion policy with low computational cost to eliminate abrupt noise of acoustic positioning system which comprises global and inertial sensors is open research question[10].

1.1 Literature Review

Direct values of inertial sensors contain high uncertainty because of underwater environment at the same time acoustic systems may produce delayed measurements and abrupt noise. If we are able to model the system below surface of water then there would not be any limitations for conventional fusion policies as kalman Filter is famous for motion estimation[11] 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[12] by involving jacobian matrix which affects computational cost as well as it can not overcome abrupt noise of acoustic sensor. If we go for non gaussian distributions then Particle filters are non linear models but have expensive computational cost because

of probabilities distribution based estimation[13]. Due to multiple hypothesis particle filter gives delayed results even when there is reliable sensory data.
Multiple techniques and algorithms[14] have been applied on wireless sensor network to localize the underwater vehicle by reducing underwater noise with purpose to accurately localize underwater vehicle. As underwater communication is done using acoustic system that is why for overcoming abrupt noise placement of acoustic systems matters to have strong signal strength[15]. Major advancements have done but collectively it is expensive system because multiple systems have to distribute below the surface of water[16]. Other than cost such systems are very complex to understand because such systems contain multiple protocols of networking furthermore there are privacy and security concerns[3].
For single onboard vehicle one approach to overcome noise is modeling of non-linearities by supervised learning[17] but this is suitable where system repeat patterns and task conditions remain almost similar between training and execution. To identify the reliability of acoustic positioning sensor is the main challenge for autonomous underwater vehicle because of long delaying in its measurements[18]. 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.
In a very recent methods for underwater fusion and localization Chame[10] proposed principle of contextual anticipation in which with every coming reliable sensor value the anticipation span resets to overcome abrupt noise and to consider the reliable sensory value with which their anticipation span reset. 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 all sensors so collective noise appear as result.

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. 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 PCBC-DIM Neural Network

PCBC-DIM is a hierarchical neural network in which predictive coding[19] is made compatible with Biased Competition[20] and that is implemented using Divisive Input Modulation[21]. 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.

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

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

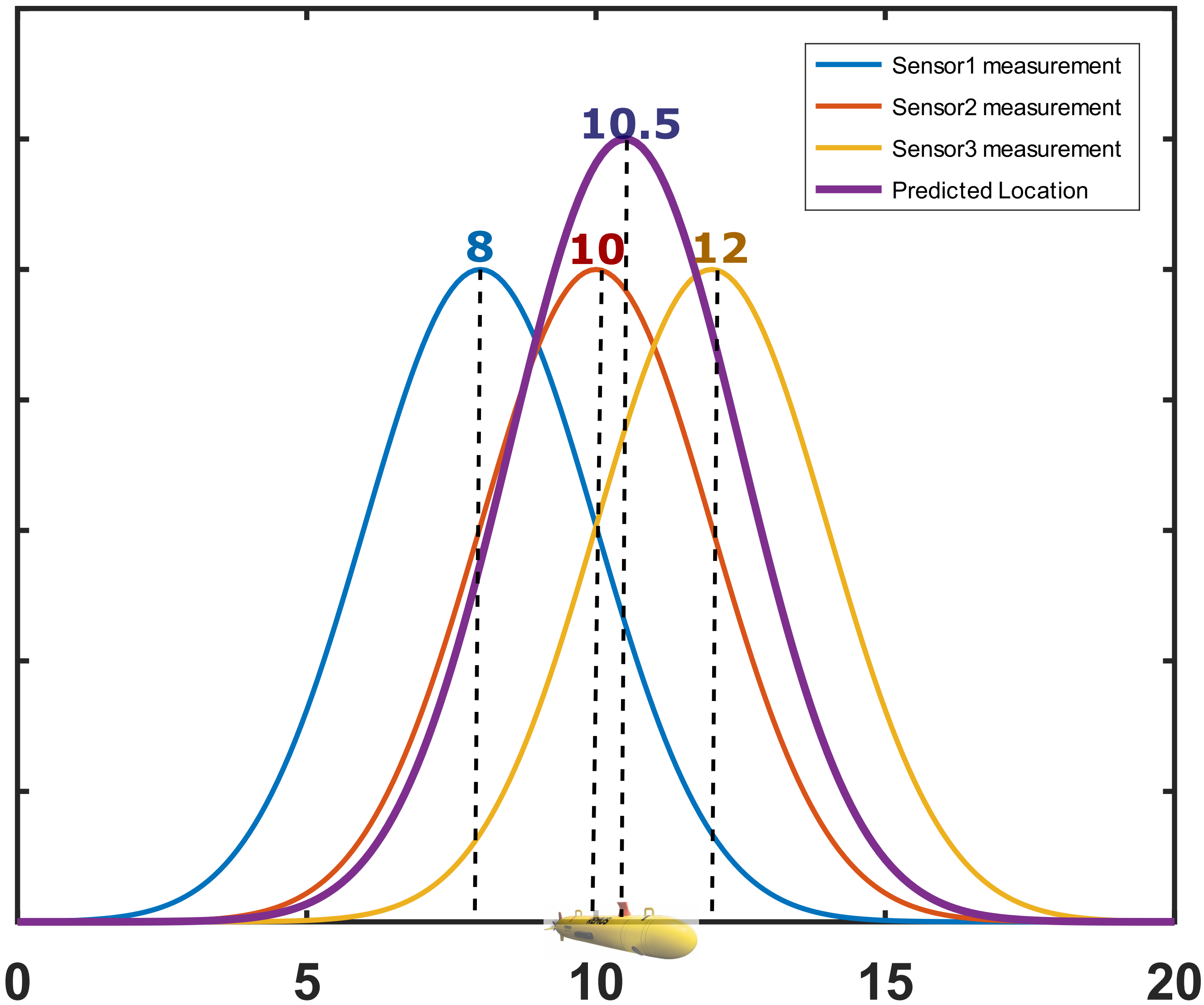


Figure 1. height of peak is showing the reconstructed results of all sensor

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

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

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

W$\Leftarrow$ [WI WG]

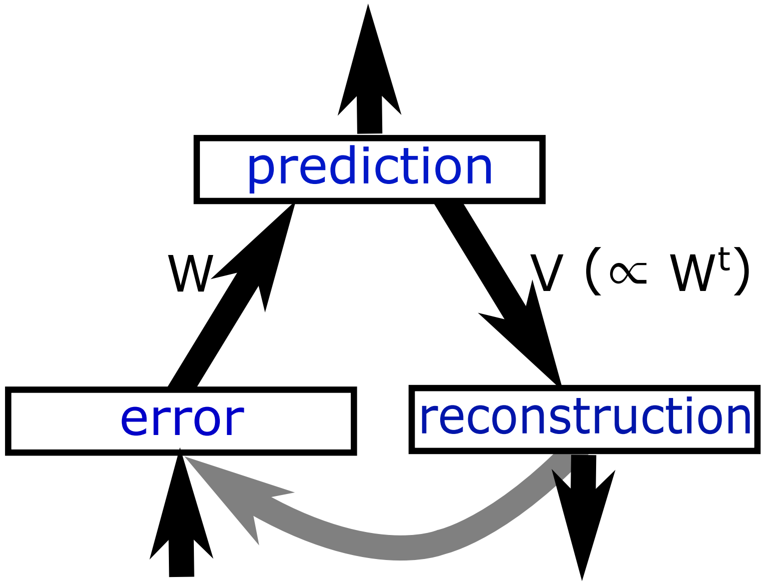


Figure 2. rectangular boxes Represents Error(e), Prediction(y) and Reconstruction(r) neuron populations. Every coming input processes from network to reconstruct the sensory data.

V$\Leftarrow$ [VI VG]
[n,m] $\Leftarrow$ *size*(W)
y $\Leftarrow$ *zeros*(1,n)
while $val \neq FinalValueOfSensor$ **do**
  if val_I is present **then** ▷ For all inputs
    $xInertial \Leftarrow Gaussian(val_I + last_I)$
  else
    $xInetial$ $\Leftarrow$zeros(:,m)
  end if
  if val_G is present **then**
    $xGlobal \Leftarrow Gaussian(val_G - last_G)$
  else
    val_G $\Leftarrow$zeros(:,m)
  end if
  x = [xInertial xGlobal]^t
  while Iterations **do**
    $r = V * y$
    $e = x \oslash (\varepsilon 2 + r) W * e$
    $y = (\varepsilon 1 + y) \otimes W * e$
  end while
  location = decode(r)
  if sum(xGlobal)!= 0 **then** ▷ As we are taking change for global sensor
    $last_G = location$
    $last_I = 0$;
  end if
end while

Algorithm for the sensor is explained

3 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[10] 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

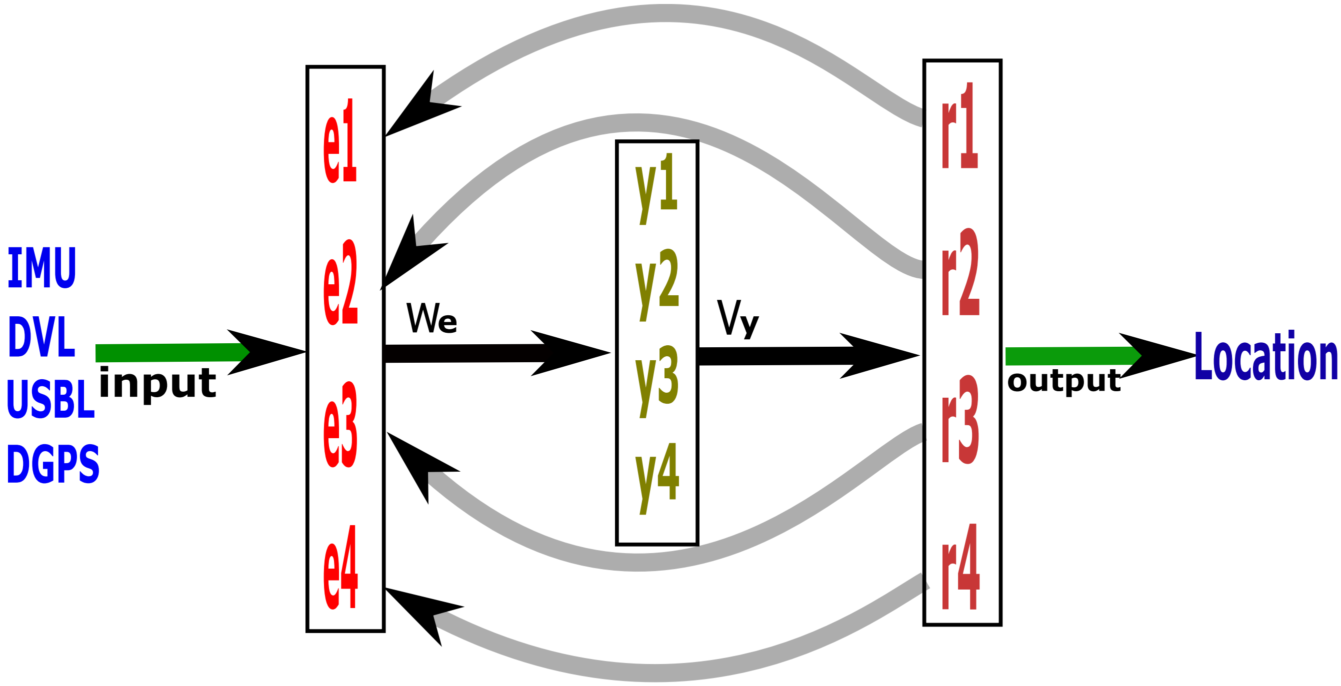
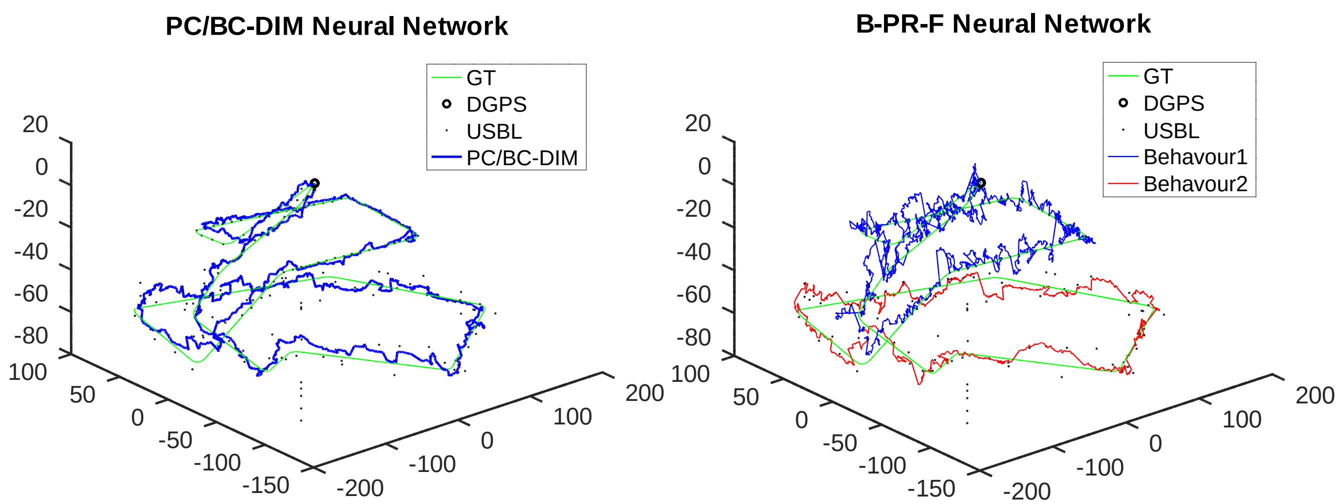


Figure 3. IMU and DVL are inertial sensors which returns instant change. USBL and DGPS are global positioning sensors which returns absolute position. e1,e2,e3 and e4 are respective errors of IMU,DVL, USBL and DGPS. Figure shows that each sensor individually reconstructing its location as well as sensory data is fusing. On the Output after iterations we obtain specific fused and standardized(less noisy) location.



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

Figure 4. Comparison of PC/BC-DIM and B-PR-F using same data in Octave

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

Figure 4 gives clear understanding of RMS and Std error

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

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 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.

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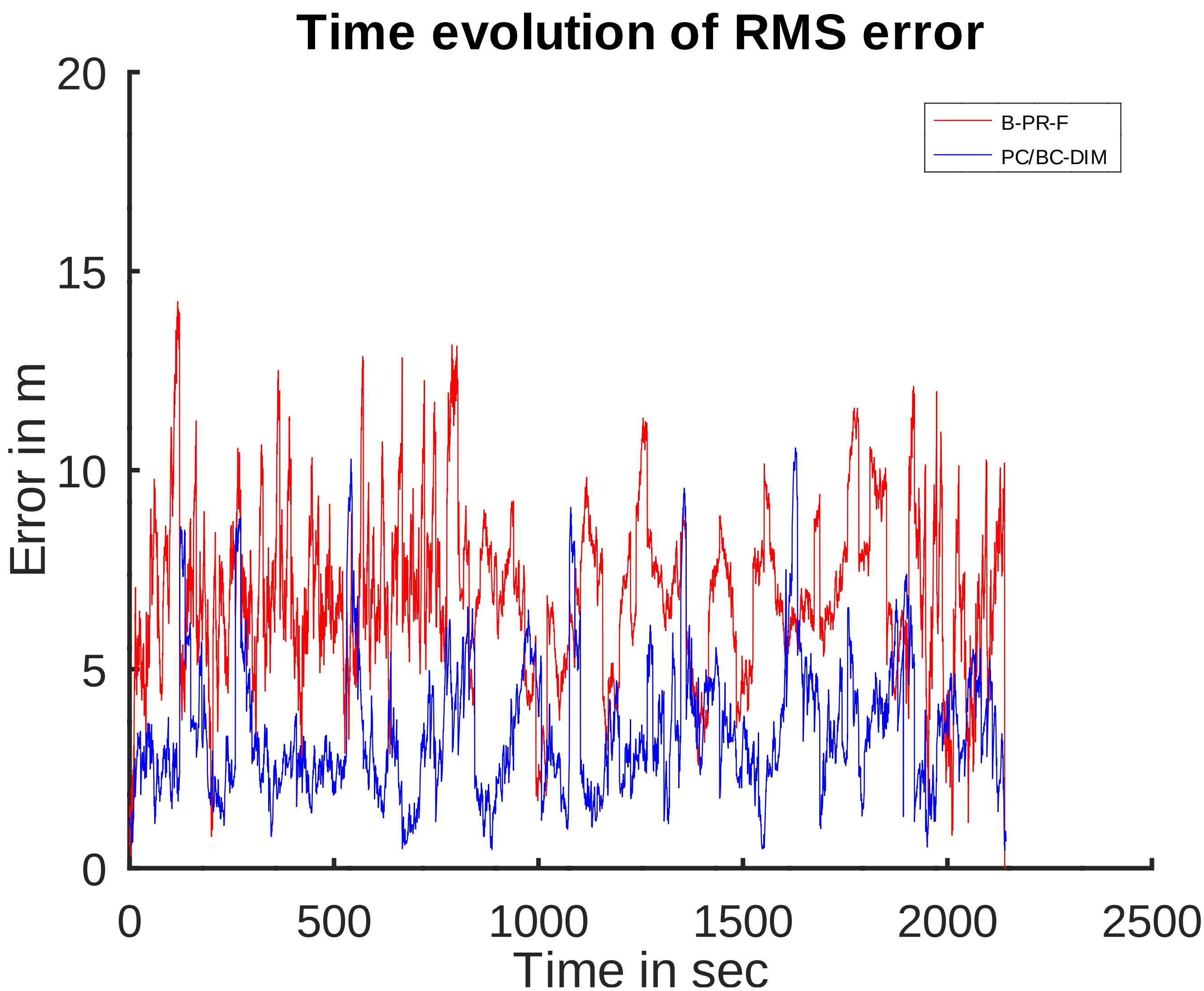

Figure 5. Comparison of PC/BC-DIM and B-PR-F using same data in Octave

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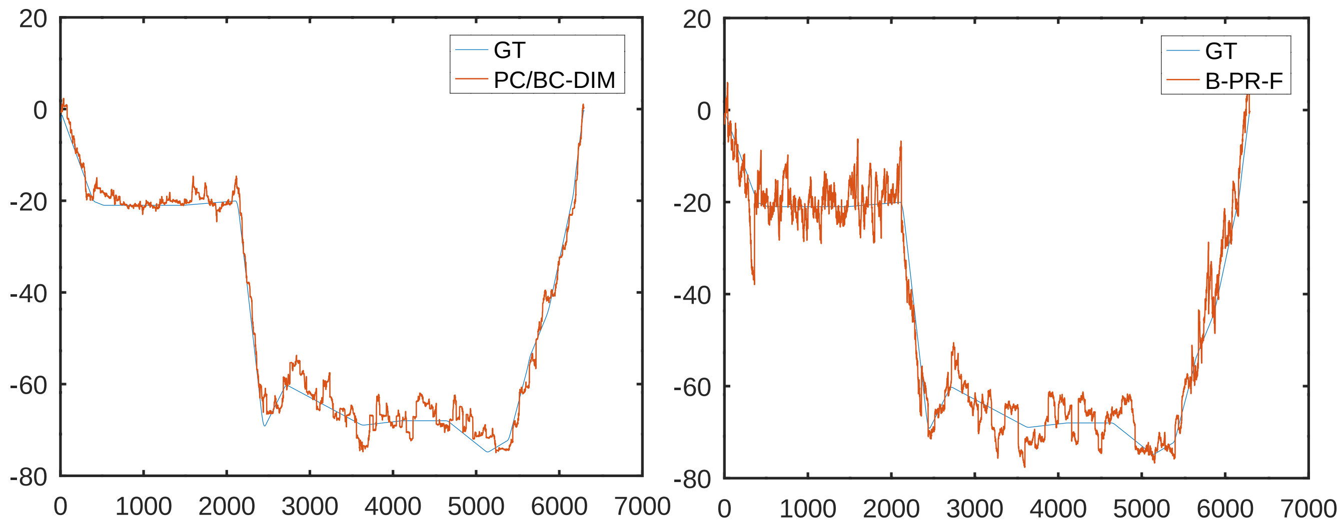

(a) PC/BC-DIM **(b)** B-PR-F.

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

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