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Estimation filtering for Deep Water Navigation ⋆

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Abstract: The navigation task for Unmanned Underwater Vehicles is made difficult in a deep water scenario because of the lack of bottom lock for Doppler Velocity Log (DVL). This is due to the operating altitude that, for this kind of applications, is typically greater than the sensor maximum range. The effect is that the velocity measurements are biased by sea currents resulting in a rapidly increasing estimation error drift. The solution proposed in this work is based on a distributed, cooperative strategy strongly relying on an acoustic underwater network. According to the distributed philosophy, an instance of a specifically designed navigation filter (named DWNF – Deep Water Navigation Filter) is executed by each vehicle. Each DWNF relies on different Extended Kalman Filters (EKFs) running in parallel on-board: one for own navigation state estimation (AUV-EKF), the other ones for the navigation state of the remaining assets (Asset-EKF). The AUV-EKF is designed to simultaneously estimate the vehicle position and the sea current for more reliable predictions. The DWNF builds in real-time a database of past measurements and estimations; in this way it can correctly deal with delayed information. An outlier detection and rejection policy based on the Mahalanobis distance associated to each measurement is implemented. The experimental validation of the proposed approach took place in a deep water scenario during the Dynamic Mongoose'17 exercise off the South coast of Iceland (June-July 2017); preliminary analysis of the results is presented.

Keywords: Deep water navigation, Cooperative navigation, Long-term navigation, Autonomous Underwater Vehicles, Marine systems, Extended Kalman filters

1. INTRODUCTION

Navigation state estimation for Unmanned Underwater Vehicles (UUV) is one of the most challenging problems to be faced in the development of Guidance, Navigation and Control (GNC) systems (Paull et al., 2014; Kinsey et al., 2006). The main reason is the impossibility of using Global Navigation Satellite Systems (GNSS) under the surface because of the radio wave absorption by the water. Dead reckoning navigation systems exploiting the integration of acceleration and velocity measurements are the solution currently widely used to address the problem. The best performance is obtained for vehicles that house on-board high grade Attitude and Heading Reference Systems (AHRS) - integrating Fiber Optics Gyroscopes (FOG) - and a Doppler Velocity Log (DVL). For UUV with this kind of navigation sensor suite, the literature reports errors as small as 0.1% of distance travelled (Hegrenæs et al., 2016). In the case of shallow water, longer duration missions, if regular surfacing is to be avoided for mission specific requirements or for energy efficiency reasons, local acoustic positioning systems, as e.g. Long BaseLine (LBL), can be installed and used to reset the drift of the estimation error.

When considering deep waters, the scenario is different: vehicles start the mission far from the bottom, and might conduct the entire mission at an altitude too high to get DVL bottom lock. Velocity measurements provided by the sensor to the navigation system are in this case biased by the sea current contribution. A dead reckoning algorithm that uses these measurements produces an estimation that, according to current strength, may be affected by an error that quickly increases. Moreover, it has to be considered that, in a deep water scenario, the deployment of acoustic beacons for a local positioning system may not be feasible.

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To solve the problem, the typical approach is based on acoustic corrections (Webster et al., 2012). This paper describes a system for navigation state estimation on each Autonomous Underwater Vehicle (AUV). The system integrates different technologies and does not rely on the deployment of dedicated beacons. The sensors used are heterogeneous and complementary to ensure a reliable navigation even when one or more of them may fail e.g. because of environmental or operational conditions. Within the considered scenario different assets, including AUVs, represent the nodes of an Underwater Acoustic Network (UAN). To address the deep water navigation task, a distributed, cooperative strategy that strongly relies on communication among the different assets, has been developed. Measurements are either triggered by or provided to the vehicle thanks to communication via acoustic modems. All used acoustic modems are equipped with Ultra Short BaseLine (USBL) heads that can determine the direction of arrival of received messages. Range measurements are obtained through the addition of a dedicated service to the UAN without the necessity of additional hardware, following the scheme described in Munafò and Ferri (2017).

The aim of this paper is to describe the algorithm that has been developed to run on-board each AUV. According to the distributed philosophy, an instance of a specifically designed Deep Water Navigation Filter (DWNF) is executed by each AUV. The paper focuses on the peculiarities and the design choices of the DWNF, which represents the core of the distributed cooperative system. The description of the interaction with the underlying UAN is limited to information required by the DWNF. UAN implementation details as well as relative performance analysis fall outside the scope of this work. Each DWNF relies on a number of Extended Kalman Filters (EKFs) running in parallel onboard: one is dedicated to own navigation state estimation (AUV-EKF), the other ones for the navigation state of the remaining assets (Asset-EKF). The AUV-EKF is designed to simultaneously estimate the vehicle position and the local sea current for more reliable predictions. In the context of this work, it is necessary to stress that all correction measurements are based on acoustics and rely on heterogeneous technology. The latest information will become available to each asset only after a considerable delay, and potentially not at all. The DWNF is hence designed to be opportunistic: it uses measurements as soon as they become available. Measurements delivered to the assets through the acoustic network may be affected by a non-negligible delay. The DWNF builds in real-time a database of all the past information; in this way, delayed measurements can be correctly used for estimation correction (Maczka et al., 2007). An outlier detection and rejection policy based on the Mahalanobis distance associated to each measurement is implemented (Hodge and Austin, 2004). This proved to be very useful to maintain a reliable estimation, even in the presence of frequent outliers.

After a development and experimental validation period in simulated deep water conditions and a dedicated engineering test (Costanzi et al., 2017), the distributed cooperative navigation strategy has been successfully implemented on the assets of the NATO STO CMRE network which included two Ocean Explorer (OEX) AUVs. The first real deep water missions took place during the Dynamic Mongoose'17 exercise off the South coast of Iceland (June-July 2017). A preliminary analysis of the experimental data is presented in this work. Results show the effectiveness of the proposed DWNF in making the OEX able to navigate underwater without the need of ground-referenced velocity measurements or periodic surfacing to get a GPS fix.

The following sections of the paper are organised as follows. Sec. 2 is dedicated to a description of the UAN underlying the system. In Sec. 3, the problem is formulated; the process and measurements models considered in the filters are introduced. Sec. 4 proposes the details of the developed system focusing on the various design choices. In Sec. 5 the experimental scenario is introduced and the validation of the described system in a real deep water scenario is addressed. Sec. 6 reports the conclusions that can be derived from the analysis presented in the paper.

2. UNDERWATER ACOUSTIC NETWORK

The proposed algorithm follows a distributed approach with one instance of the DWNF locally running on each AUV. The DWNF relies on the availability of different acoustic measurements to correct the navigation state estimation: position, direction of arrival of acoustic messages, and range. The possibility of using these corrections is provided by an UAN that connects the AUVs with various cooperating assets. In this scenario, the AUVs and the assets represent the network nodes. In addition to the AUVs and the support ship, either static or mobile surface gateway nodes are included among the assets to ensure an extended and reliable functioning of the UAN. In particular:

- **Position -** the AUV position is measured by means of a dedicated system mounted on the support ship. It is a Kongsberg HiPAP capable of localising the transponders mounted on the vehicles. The relative position measurements determined by the HiPAP are integrated with the ship position and attitude data to compute the AUV absolute position. This information, available on the support ship, is shared with the AUV via the UAN. The AUV can exploit the information for the correction of the navigation state.
- **Direction of arrival (DOA) -** each time that a message is received by the acoustic modems mounted on the AUVs, a measurement of the direction of arrival is provided by the USBL system. In order to correct the navigation state, the position of the transmitting asset has to be measured or estimated. With the aim of making this information available to the AUV, each asset periodically shares through the acoustic network an estimation of its own position.
- **Range -** the measurement of relative distance directly depends on the UAN. It is based on an asynchronous exchange of messages and relies on a navigational layer on top of the acoustic network. The implementation details are described in Munafò and Ferri (2017). In addition, as for the direction of arrival measurements, the position of the remote asset is necessary to apply range corrections. This information is shared using the UAN.

To summarise, all the information needed by the DWNF to work properly is delivered to the vehicle through the acoustic network according to a Time Division Multiple Access (TDMA) policy. It is worth to highlight that the UAN, even if exploited for navigation purposes, is not implemented for this reason. On the contrary, it is an already existing and fully operational acoustic network developed to address the mission goals. Addition of information for the sake of navigation has a minimal impact on normal network operation. The localization data are transmitted only when possible and only when it does not interfere with the delivery of higher priority messages.

The following sections focus on how this information is used on each AUV to calculate in real-time an estimation of the navigation state.

3. PROBLEM FORMULATION

Within the described operating scenario, the vehicle is considered to be equipped with a set of navigation sensors commonly used in the underwater domain: a tri-axial Inertial Measurement Unit (IMU), a pressure sensor, a DVL, an USBL system with modem capabilities and a GPS receiver (when on the surface). All the devices are calibrated in such a way that the measurements they provide are aligned with the body-fixed reference frame, which is defined as in Antonelli (2014).

The proposed DWNF exploits all the measurements gathered on-board the vehicle as soon as they are available. For the purposes of the following discussion, it is worth to make a distinction between *proprioceptive* and *exteroceptive* measurements. The former are quantities acquired by means of on-board sensors which refer to the vehicle motion; therefore, they can be processed without external information and their availability depends only on whether the instrument is working or not. Exteroceptive measurements are either relative to aiding sources located in the environment or acquired and communicated to the vehicle by external support systems. In both cases, they require data exchange with external devices before being processed, and their availability is thus highly dependent on the UAN. In this work, the proprioceptive measurements made available to the DWNF from the on-board sensors are the orientation of the vehicle (heading ψ, pitch θ and roll ϕ), the depth z and the velocity over water provided as module s_{ow} and course angle θ_{ow}. The exteroceptive measurements are represented by the information received through the communication network listed in Sec. 2, in addition to the GPS position.

3.1 Process model

Since the depth in the underwater environment can be reliably measured on-board each asset through the pressure sensor and given the relatively small operational area (within few kilometres on the horizontal plane and hundred of metres of depth), the navigation problem can be reduced to the horizontal plane. Let $\mathbf{x}_k = [x_k \; y_k]^T$ and $\mathbf{v}_k = [u_k \; v_k]^T$ be respectively the position of the vehicle and the velocity of the sea current in the operating area at time k, with respect to the North-East-Down (NED) reference system. Assuming the local sea current to be constant in that frame, the 2D kinematic model is given by the following equations:

$$
\begin{aligned}
x_{k+1} &= x_k + \Delta t \left(\tilde{s}_{\mathrm{ow},k} \cos \tilde{\theta}_{\mathrm{ow},k} + u_k\right) \\
y_{k+1} &= y_k + \Delta t \left(\tilde{s}_{\mathrm{ow},k} \sin \tilde{\theta}_{\mathrm{ow},k} + v_k\right) \\
u_{k+1} &= u_k + \Delta t \, \nu_u \\
v_{k+1} &= v_k + \Delta t \, \nu_v
\end{aligned} \quad , \tag{1}
$$

where Δt is the sampling period. The uncertainty in the sea current dynamics is modelled by $\nu_u \sim \mathcal{N}(0, Q_u)$ and $\nu_v \sim \mathcal{N}(0, Q_v)$. The inputs are represented by the noisy velocity over water measurements:

$$
\begin{aligned}
\tilde{s}_{\mathrm{ow},k} &= s_{\mathrm{ow},k} + \nu_s \\
\tilde{\theta}_{\mathrm{ow},k} &= \theta_{\mathrm{ow},k} + \nu_\theta
\end{aligned} \; ,
$$

where $s_{\mathrm{ow},k}$ and $\theta_{\mathrm{ow},k}$ are the actual values of the module and of the course angle, respectively, and $\nu_s \sim \mathcal{N}(0, Q_s)$ and $\nu_\theta \sim \mathcal{N}(0, Q_\theta)$ are the corresponding noises.

3.2 Measurement model

When the vehicle is on the surface, it has access to the GPS signal, providing a non-diverging, absolute position information. The GPS observations are expressed as North-East coordinates with respect to the origin of the NED frame:

$$
\mathbf{z}_{\mathrm{GPS}} = \begin{bmatrix} x_k \\ y_k \end{bmatrix} + \boldsymbol{\eta}_{\mathrm{GPS}}. \tag{2}
$$

The same model is valid also for the HiPAP position estimate sent to the vehicle from the support vessel:

$$
\mathbf{z}_{\mathrm{HiPAP}} = \begin{bmatrix} x_k \\ y_k \end{bmatrix} + \boldsymbol{\eta}_{\mathrm{HiPAP}}. \tag{3}
$$

Both measurements are affected by Gaussian additive noises $\boldsymbol{\eta}_{\mathrm{GPS}} \sim \mathcal{N}(\mathbf{0}, \mathbf{R}_{\mathrm{GPS}})$ and $\boldsymbol{\eta}_{\mathrm{HiPAP}} \sim \mathcal{N}(\mathbf{0}, \mathbf{R}_{\mathrm{HiPAP}})$, respectively.

Upon the reception of an acoustic message from the i-th network asset, the on-board USBL measures the DOA of the signal expressed in its own reference frame. The DOA is compensated for the vehicle attitude (pitch and roll angles) to determine the relative bearing between the two nodes. Knowing the position of the transmitter in the navigation frame, the relative bearing angle can be modelled as the difference between the direction of the line joining the sender and the receiver with respect to the North axis and the vehicle heading:

$$
z_{\mathrm{USBL}} = \operatorname{atan2}(\tilde{y}_{i,k} - y_k, \tilde{x}_{i,k} - x_k) - \tilde{\psi}_k + \eta_{\mathrm{USBL}}, \tag{4}
$$

where $\eta_{\mathrm{USBL}} \sim \mathcal{N}(0, R_{\mathrm{USBL}})$ is the noise assumed affecting the USBL measurement. The position of the sender $\tilde{\mathbf{x}}_{i,k} = [\tilde{x}_{i,k} \; \tilde{y}_{i,k}]^T$ and the vehicle heading $\tilde{\psi}_k$ are defined as following:

$$
\begin{aligned}
\tilde{\mathbf{x}}_{i,k} &= \mathbf{x}_{i,k} + \boldsymbol{\eta}_{\mathbf{x}_i}, \\
\tilde{\psi}_k &= \psi_k + \eta_\psi,
\end{aligned}
$$

where $\mathbf{x}_{i,k}$ and ψ_k are the corresponding actual values, $\boldsymbol{\eta}_{\mathbf{x}_i} \sim \mathcal{N}(\mathbf{0}, \mathbf{R}_{\mathbf{x}_i})$ is the uncertainty associated to the position of the i-th asset and $\eta_\psi \sim \mathcal{N}(0, R_\psi)$ is the noise affecting the heading.

The distance with respect to the i-th asset provided by the algorithm in Munafò and Ferri (2017) can be projected on the horizontal plane by compensating the relative depth between the sender and the receiver:

$$
r_{i,k}^{2D} = \sqrt{(r_{i,k}^{3D})^2 - (z_{i,k} - z_k)^2}.
$$

The depth $z_{i,k}$ and z_k of the transmitter node and of the AUV, respectively, are assumed to be accurately measured by the corresponding asset and shared through the acoustic network. Hence, the 2D range can be computed onboard the AUV and used to feed the DWNF. Given the position of the remote asset, the range measurement can thus be modelled as following:

$$z_{\text{rng}} = \sqrt{(\tilde{x}_{i,k} - x_k)^2 + (\tilde{y}_{i,k} - y_k)^2} + \eta_{\text{rng}}, \tag{5}$$

where $\eta_{\text{rng}} \sim \mathcal{N}(0, R_{rng})$ is the corresponding noise.

4. DEEP WATER NAVIGATION FILTER

The proposed DWNF is specifically designed to deal with the typical issues related to the acoustic-based measurements, such as time irregularity, latency and presence of outliers (Paull et al., 2014).

Defining the state vector $\boldsymbol{\xi}_k = [\mathbf{x}_k^T \ \mathbf{v}_k^T]^T$, the input vector $\mathbf{u}_k = [s_{\text{ow},k} \ \theta_{\text{ow},k}]^T$ and the process noise vector $\boldsymbol{\nu}_k = [\nu_s \ \nu_\theta \ \nu_u \ \nu_v]^T$, Equation (1) can be arranged in the compact form

$$\boldsymbol{\xi}_{k+1} = f(\boldsymbol{\xi}_k, \mathbf{u}_k, \boldsymbol{\nu}_k). \tag{6}$$

Similarly, Equations (2), (3), (4) and (5) can be rewritten as

$$\boldsymbol{z}_{*,k} = h_*(\boldsymbol{\xi}_k, \boldsymbol{\eta}_{*,k}) \tag{7}$$

by including all the respective noise terms in a vector $\boldsymbol{\eta}_{*,k}$ associated to each equation.

The navigation algorithm is hence realised by fusing all the information with an Extended Kalman Filter (EKF). In this framework, the *prediction* step is based on the Equation (6), while the *update* step exploits the output models described by Equations (2), (3), (4) and (5), arranged as in (7). By means of the designed EKF (AUV-EKF), the DWNF can properly manage the time irregularity of the exteroceptive measurements, performing the update step with the corresponding output model each time a new data is available.

4.1 Tracking of network assets

In order to exploit DOA and range measurements, the DWNF requires the knowledge of the position of the sender asset (Equations 4 and 5). Since localisation data are exchanged as normal messages of the acoustic network, it can happen that the remote node position is not available onboard the vehicle at the same time of the aforementioned quantities. A set of EKFs, one for each network node, runs in parallel to the AUV-EKF in order to track the position $\mathbf{x}_{i,k} = [x_{i,k} \ y_{i,k}]^T$ of the i-th asset. Each of these filters (Asset-EKF) employs a purely kinematic model for the asset motion in the prediction step:

$$\begin{aligned} x_{i,k+1} &= x_{i,k} + \Delta t \, v_{x_i,k+1} \\ y_{i,k+1} &= y_{i,k} + \Delta t \, v_{y_i,k+1} \\ v_{x_i,k+1} &= v_{x_i,k} + \Delta t \, \nu_{v_{x_i}} \\ v_{y_i,k+1} &= v_{y_i,k} + \Delta t \, \nu_{v_{y_i}} \end{aligned} \, , \tag{8}$$

where $\mathbf{v}_{i,k} = [v_{x_i,k} \ v_{y_i,k}]^T$ is the asset velocity in the North-East plane and $\nu_{v_i} = [\nu_{v_{x_i}} \ \nu_{v_{y_i}}]^T \sim \mathcal{N}(0, \mathbf{Q}_{v_i})$ accounts for the uncertainties in the velocity dynamics. In the update step, the position of the node i ($\tilde{\mathbf{x}}_{i,k}$) is fed to the corresponding Asset-EKF whenever it is received and integrated according to the Equation (2). Every time a DOA or range observation is received, the DWNF cherry-picks the estimated position at the time of the incoming measurement from the Asset-EKF of the sender, and uses it in Equation (4) or (5) to compute the predicted output.

4.2 Outliers rejection

Acoustic-based measurements are frequently affected by outliers which can cause high estimation errors or, in the worst case, the divergence of the filter. To overcome this problem, the DWNF adopts an outliers detection and rejection policy based on the Mahalanobis distance (Hodge and Austin, 2004). An incoming acoustic measurement $\mathbf{z}_{*,k}$ is considered valid iff the condition

$$\sqrt{\mathbf{e}_{*,k}^T \, \mathbf{S}_k^{-1} \, \mathbf{e}_{*,k}} \leq T_* \tag{9}$$

holds. The residual $\mathbf{e}_{*,k} = \mathbf{z}_{*,k} - h_*(\hat{\boldsymbol{\xi}}_{k|k-1})$ is defined as the difference between the observation and the predicted output, obtained by propagating the predicted estimate $\hat{\boldsymbol{\xi}}_{k|k-1}$ through the proper measurement model. The matrix $\mathbf{S}_k = \mathbf{H}_{*,k} \, \hat{\mathbf{P}}_{k|k-1} \, \mathbf{H}_{*,k}^T + \mathbf{R}_*$ represents the covariance matrix of the residual, in which $\mathbf{H}_{*,k}$ and $\hat{\mathbf{P}}_{k|k-1}$ are the linearisation of the measurement model $h_*(\cdot)$ with respect to the state vector $\boldsymbol{\xi}_k$ and the error covariance matrix of the predicted estimate, respectively. A measurement is thus identified as an outlier if its error with respect to the predicted output is not coherent with the uncertainty given by the residual covariance matrix within the bound defined by the threshold value T_*. For each exteroceptive measurement, the value of threshold T_* is derived on the basis of an extensive analysis of historical data collected during past NATO STO CMRE experimental campaigns.

4.3 Latency management

Measurements delivered through the acoustic network may be affected by a non-negligible delay, mainly because of the medium characteristics and the adopted TDMA scheme (Śliwka et al., 2017). To deal with such an issue, the DWNF builds in real-time a database containing the history of all the past estimates, proprioceptive and exteroceptive measurements. In the case that at time k the vehicle receives a new measurement $\mathbf{z}_{*,k-N}$ associated with a previous timestamp $k - N$, the DWNF rolls back in time and uses the delayed measurement to compute the past corrected estimate with the EKF update step:

$$\begin{aligned} \hat{\boldsymbol{\xi}}_{k-N|k-N} &= \hat{\boldsymbol{\xi}}_{k-N|k-N+1} + \mathbf{K}_{k-N} \, \mathbf{e}_{*,k-N} \\ \hat{\mathbf{P}}_{k-N|k-N} &= (\mathbf{I} - \mathbf{K}_{k-N} \, \mathbf{H}_{*,k-N}) \, \hat{\mathbf{P}}_{k-N|k-N+1} \end{aligned} \, , \tag{10}$$

where $\mathbf{K}_{k-N}$ is the associated Kalman gain. This result is then propagated forward up to time k using sequentially all the proprioceptive and exteroceptive measurements following the time $k - N$ contained in the database, overwriting the previous estimates.

5. RESULTS

5.1 Experimental Scenario

The proposed system was validated in real-time in a deep water scenario between June 26th and July 6th, 2017 during a NATO operational exercise, the Dynamic Mongoose'17 experimentation, that took place off the South coast of Iceland. Several missions were carried out, each one involving a different configuration of the NATO STO CMRE UAN. From the perspective of this work, the most remarkable achievement during the experiment was that the OEX AUVs exploited the described DWNF to navigate in a deep water area without the necessity of GPS position fix for an entire day of operations.

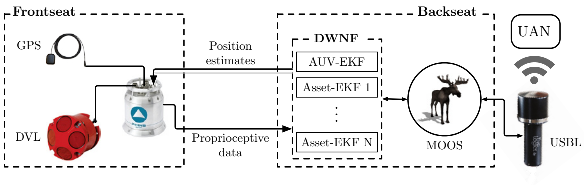

Fig. 1. Fronseat/Backseat architecture description.

The OEX on-board software architecture shown in Fig. 1 is based on the Frontseat/Backseat paradigm (Eickstedt and Sideleau, 2010). The navigation functionalities of the AUV are executed by a iXblue PHINS integrated with the frontseat. It filters the raw signal of the sensors to compute a navigation state estimation. The proposed DWNF is implemented on the backseat within a MOOS architecture (Benjamin et al., 2010). Proprioceptive measurements are periodically (1 Hz) communicated through the vehicle bus by the frontseat. Exteroceptive measurements are available through the UAN by means of the USBL modem. The estimations computed by DWNF on the backseat are communicated to the frontseat, that exploits them to refine the navigation state as they were acoustic position fixes (i.e. LBL, USBL). Despite different filters were running in parallel, no issue related to computational load was experienced.

Among the various missions that took place during the Dynamic Mongoose'17 experimentation, the one carried out on July 5th, 2017 is described in this work. This trial is particularly meaningful because it was specifically dedicated to the performance evaluation of the proposed DWNF. To this aim, the delivery of HiPAP observations to the vehicle was intentionally inhibited for long periods of time. It is to underline that HiPAP provides the most informative measurement for localisation purposes (position). Moreover, the trial was conducted in an area where the bottom lock was available (about 130 m of depth) in order to have a reliable Reference Path (RP) for the validation of the DWNF. It is worth to remark that the velocity over ground was not integrated in the DWNF, which exploited only the velocity over water measurements.

In the selected mission, in addition to one OEX (the one called Groucho), two assets were involved: the support vessel (NRV Alliance, ID=1) and a static node (a gateway buoy, ID=10). The mission lasted more than 4 hours for a total travelled distance of about 16 kilometres at 80 metres of depth. Fig. 2 shows the mission scenario. NRV Alliance, whose path is reported with the red line, performed racetracks around the OEX operational area. The gateway buoy was anchored in a fixed position, shown in magenta. The OEX Groucho predefined mission consisted in travelling along a rectangular-shaped racetrack. The

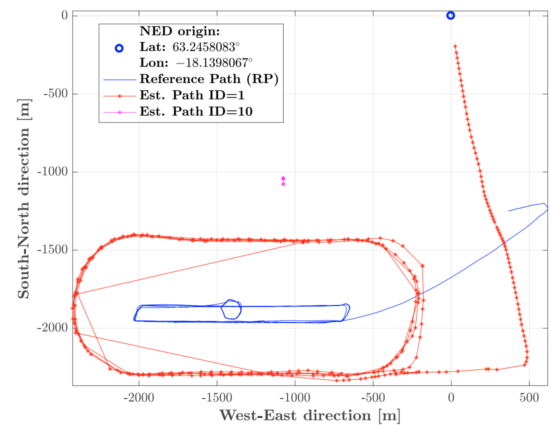

Fig. 2. Scenario for the July 5th, 2017 mission.

vehicle executed about 4 laps underwater before emerging and being recovered. The vehicle RP, obtained exploiting the velocity over ground measurements, is represented with the blue line in Fig. 2).

5.2 Results analysis

Fig. 3 reports the occurrences of the various measurements during the mission time. The HiPAP line shows in red the measurement occurrences available on NRV Alliance and, in black, the ones that were communicated to the OEX. During long (more than a hour) time spans, position measurements were intentionally not sent to the OEX Groucho. GPS measurements are available at the begin-

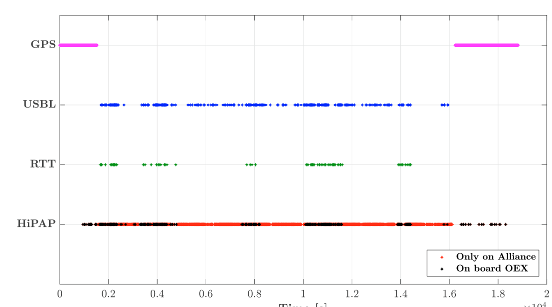

Fig. 3. Measurement occurrences during the mission.

ning and at the end of the mission when the vehicle was on the surface. USBL line refers to DOA measurements from one of the two additional assets. Range line refers to range measurements with respect to one of the two additional assets. A summary of measurements related to either NRV Alliance or to the Gateway buoy is reported in Tab. 1 with the outliers percentage with respect to the total quantity of measurements.

In Fig. 4 the HiPAP measurements on the horizontal plane during each of the executed laps are reported. The plots

Table 1. Summary of measurements received by the OEX Groucho.

Type	Number	Outliers[# (%)]	Used
GPS	3720	-	3720
HiPAP	386	13 (3.4%)	373
USBL	306 (ID=1), 27 (ID=10)	23 (6.9%)	310
Range	61 (ID=1), 8 (ID=10)	0 (0.0%)	69

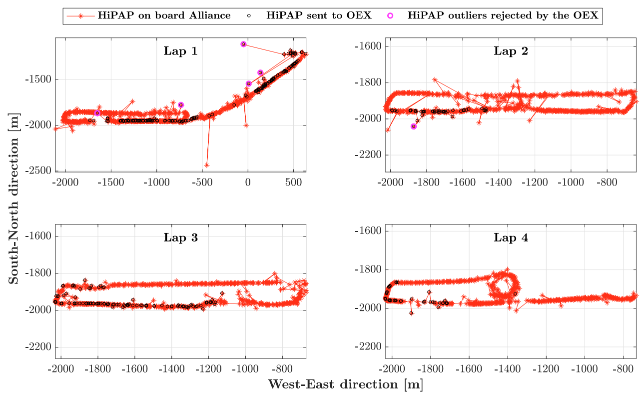

Fig. 4. HiPAP measurements during the mission.

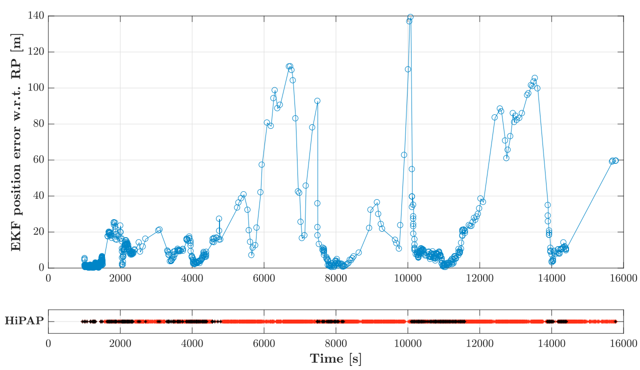

Fig. 5. Estimation error with respect to the reference path.

show that the vehicle received only a small subset (black circles) of the whole cluster of HiPAP measurements acquired on-board the vessel (red stars). Among the received subset, the DWNF correctly identified and rejected several noticeable outliers, indicated with magenta circles. No false positive (good measurement erroneously identified as outlier) is evident.

In order to quantitatively evaluate the estimation error, Fig. 5 reports the position error during the mission. The HiPAP measurements at the corresponding time on NRV Alliance (red stars) and on-board the OEX Groucho (black stars) are also reported in the lower part of the plot. Despite the lack of HiPAP measurements for considerably long mission periods, the DWNF, by exploiting complementary measurements, is able to provide a reliable estimate of the navigation state. The proposed DWNF demonstrated to be able to maintain the position error lower than 150 metres. In the presented scenario, this is considered as sufficiently low to navigate without the necessity of emerging to get the GPS.

6. CONCLUSION

This work described a Deep Water Navigation Filter able to exploit a number of localisation measurements. The filter was deployed on the NATO STO CMRE AUVs to support their navigation during the Dynamic Mongoose'17 experiment. The preliminary results presented are encouraging in demonstrate the validity of the proposed method. Deeper analysis on the experimental data collected are currently on-going for a thorough characterisation of the deep water navigation system from the point of view of the whole network and in different environmental conditions. Future works will focus on validating the water current estimation through dedicated experiments.

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