Experimental evaluation of outliers filtering techniques in networked acoustic localisation systems

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Abstract: Localisation-aware underwater networks are gaining increasing attention in the marine robotics community thanks to their ability of providing navigational services. This can be beneficial in a number of applications, as for instance to support the navigation of Autonomous Underwater Vehicles (AUVs) when traditional aiding systems are impractical or not cost effective. However, the unreliability of the acoustic channel, together with the additional overhead and constraints introduced by the network itself, result in localisation measurements that are intrinsically sporadic. This makes the outlier filtering problem of localisation measurements obtained through networked underwater systems particularly important and challenging. This paper uses experimental data to compare the integration of two different outlier filtering methodologies in an existing network-aided AUV navigation filter. The first method aims at pre-filtering the measurements to identify and discard potential outliers before they are fused in the navigation filter. The second one modifies the correction step of the Kalman filter to integrate measurements in an outlier-robust way. Results show that when the navigation filter is made outlier-robust the navigation performance increases and the system becomes less sensitive to tuning, a key characteristic for fielded systems.

Keywords: Kalman filtering techniques in marine systems control; Autonomous Underwater Vehicles; Acoustic-Based Networked Control and Navigation

1. INTRODUCTION

The deployment of Autonomous Underwater Vehicles (AUVs) is on an exponential growing trend. Recent advances in robotics are improving efficiency while lowering costs, and this is translating into a reduction of the risks involved in marine operations. Key to this continued improvement is the ability of the vehicles to navigate with an increased navigational precision. The absence of some sort of an external positioning reference such as the Global Positioning System (GPS) makes underwater navigation a challenging task. Underwater vehicles mainly rely on their own proprioceptive information (dead-reckoning), as obtained from Doppler Velocity Logs (DVLs), Inertial Navigation Systems (INSs), etc. Additional aids ranging from deploying fixed beacons (Long Base-Line, LBL), to geo-referencing with respect to terrain features, to periodically surfacing to obtain a GPS fix, are typically used to bound the unavoidable ever growing error that INSs are subject to (Paull et al., 2014). The limitations of these traditional approaches are evident. The vehicle might need to interrupt the mission to obtain a GPS fix, carry specialised sensors and/or limit its operations to specific areas. Some scenarios, however, allow for a different approach where a vehicle can exploit the presence of an underwater acoustic network as a supporting infrastructure to obtain localisation information through communication with the network's nodes. Starting from the concept of Moving LBL (MLBL)

presented in Vaganay et al. (2004), the idea of using a group of underwater vehicles to improve the navigational capabilities of each member has received increasing attention, and the possibility of obtaining localisation information as the byproduct of the communication between fixed and mobile underwater sensor nodes has been studied and experimentally evaluated (Cruz et al., 2013; Chen and Pompili, 2013; Munafò et al., 2014; Braga et al., 2016). Recently, the usage of a fully operational acoustic network to support the navigation of AUVs has been investigated in Munafò and Ferri (2017), where a ranging algorithm that exploits an existing networked communication system in an opportunistic manner is presented. With this approach, called Net-LBL, the distance between two nodes is evaluated based on the two-way travel time (TWTT) of an asynchronous message exchange between the considered nodes. The navigational service does not rely on specific hardware requirements or on stable-precision clock making the system particularly convenient for inexpensive vehicles, and in scenarios where there is the need to limit costs. The availability of localisation-aware networks becomes specifically critical for small-size, low-capability vehicles that do not have the option of carrying bulky sensors or specialised equipment. Building on this insight, Fenucci et al. (2018) reports some preliminary results on the development of an AUV-only localisation-aware network. The underlying idea is that when a sufficient number of AUVs can be deployed together, they can be organised to relay

localisation data. This paper expands this previous work and focuses on the analysis of the acoustic ranging performance, and on how to deal with wrong measurements to maximise the achievable navigation performance. The presence of outliers in acoustic range measurements might be due to a number of reasons (Munafò and Ferri, 2017; De Palma and Indiveri, 2017; Webster et al., 2012). In particular, when the acoustic signal bounces off the sea surface and/or sea bottom multiple times before arriving to the receiver (acoustic multi-path), this makes it appear as if transmitter and receiver are further away, creating a multi-modal error distribution. In the case of TWTT-based algorithms, another potential source of error is introduced by the specific implementation on the platforms. On non-dedicated, non-real time platforms, occasional delays due to the operating system latency can in fact arise during the TWTT measurement process, resulting in an overly increased distance between the nodes. Despite the vast literature in the outliers filtering field (see for instance Hodge and Austin (2004) and references therein), an optimal solution does not exist, and the choice of a filtering technique strongly depends on the specific application. This becomes particularly critical in the underwater domain, where the quality and the availability of the measurements is influenced not only by the technologies or the algorithms employed, but also by rapidly changing environment conditions.

This paper addresses the outlier filtering problem from a practical perspective and describes the motivations that drove the authors to a specific solution, suitable for a scenario where outliers affect measurements that are sporadic. A performance analysis of the overall AUV navigation based on experimental data is provided to support the final choice, showing the benefits of the selected outlier filtering strategy.

The remainder of the paper is organised as follows: Sec. 2 briefly describes the acoustic network and the vehicle's navigation system. Sec. 3 presents the outliers filtering problem applied to the considered scenario, motivating the solution adopted and Sec. 4 supports the discussion with a performance evaluation using experimental data with simulated outliers. Finally, Sec. 5 reports the conclusion.

2. THE AUV NETWORK

The AUV network considered in this work is composed of heterogeneous AUVs with different sensors capabilities. These robots, when deployed in a region of interest, can autonomously move to change the network geometry in response to environmental change (Caiti et al., 2012) or mission goals. During the mission the vehicles share data/information and fuse them to improve the overall mission performance. Key element of the network is the ecoSUB AUV (Phillips et al., 2017). The ecoSUBs are low-cost vehicles developed in two variants: a small (< 1 m length, 4 kg), 500 m rated model, ecoSUBμ5, and a larger one (1 m length, 12 kg) available in both the 500 m and the 2500 m rated version, ecoSUBm5 and ecoSUBm25, respectively (see Fig. 1). The ecoSUBs can be fitted with a range of sensor payloads, including Conductivity-Temperature-Depth (CTD), altimeters and acoustic modems. At the same time, the small size and limited cost of the vehicle limits the number and quality of navigation sensors

Fig. 1. The ecoSUBμ5 (first four on the left) and eco-SUBm5 (right) AUVs.

that can be mounted on-board. Typical navigation sensors include GPS, altimeter, pressure sensor and a low cost Inertial Measurement Unit (IMU). Both variants of the vehicle can carry a small acoustic modem and can hence be used as nodes of an underwater acoustic network. One interesting feature of the ecoSUBμ5 lies in its pitching ability. Thanks to the battery movement the vehicle is able to pitch up to ± 80 deg. This makes it possible for the vehicle to act as a gateway node when on surface, keeping its satellite antenna well out of the water and the acoustic modem fully submerged. The acoustic modems that have been currently integrated on the ecoSUBs are the miniature, low-cost, low-power acoustic modems developed at Newcastle University. These modems operate in the acoustic frequency band 24–28 kHz and have a maximum nominal range of about 2 km. The modems support broadcast and unicast messages. In this last case, an acknowledgement can be required and the transmitter is able to measure the range to the receiver to a resolution of 10 cm. The nano-modems support the physical layer of the communication network. The rest of the network stack includes a Medium Access Control (MAC) layer that can be user-selected between Time Division Multiple Access (TDMA) and Carrier Sensing Multiple Access (CSMA). The MAC is responsible for sharing the acoustic channel between the different nodes of the network. Above the MAC layer, the network includes a localisation module that provides a measure of the distance between the vehicle and another network node. Two alternative ranging algorithms have been implemented: LBL and Net-LBL. The former implements a classic LBL acquisition cycle exploiting the native ranging functionality provided by the nano-modems: each vehicle sends, in sequence, a unicast message with an acknowledgment request (ping) to all the surface nodes in the network, and obtains the range weighting the measured TWTT with an estimate of the speed of sound. The Net-LBL algorithm is described in Munafò and Ferri (2017). Transmission and reception timestamps of an asynchronous message exchange between the vehicle and another network node are converted into range measurements. It is worth remarking that, in this architecture, the localisation module is a *service* offered by the network: the communication is exploited to acquire localisation data in an opportunistic way, without impacting the normal functioning of the network. If needed, information exchanged between the vehicles to implement the ranging algorithm are piggybacked with communica-

tion data to reduce the transmission overhead.Finally, the network provides a priority-based message queuing system to prioritise critical messages.

2.1 The AUV navigation filter

The range measurements provided by the network are used by the node navigation filter. This filter calculates an estimate of the node's position during a prediction phase. The prediction phase (dead-reckoner) is based on a simple kinematic model which defines the position of the $i - th$ vehicle in the local navigation frame at time $k + 1$ as:

$$\begin{aligned} x_i(k+1) &= x_i(k) + v_i(k)\cos(\theta_i(k))dt + \nu_x \\ y_i(k+1) &= y_i(k) + v_i(k)\sin(\theta_i(k))dt + \nu_y \end{aligned} \quad (1)$$

where dt is the sampling period. The input signals are the surge speed v_i and the heading θ_i. Both of them are affected by noise, modelled as white, Gaussian random variables with zero mean and covariance Q_v and Q_θ, respectively. The heading is obtained directly from the on-board compass, while the surge speed v_i is crudely estimated from the rotational speed ω_i of the propeller considering a constant linear model:

$$v_i = K_{\text{prop}}\,\omega_i, \quad (2)$$

where the constant K_{prop} was experimentally characterised through tank tests. Note that using such a model the quantity v_i represents the *surge speed over water* rather than the surge speed of the vehicle, as assumed in (1). This means that the prediction is subject to drifts in presence of environmental perturbations such as water currents, wind, etc. Fictitious Gaussian process noises ν_x and ν_y with zero mean and covariance Q_x and Q_y, respectively, are added in (1) to take into account these unmodelled dynamics (Simon, 2006). Alternatively, model (1) could be augmented to include sea-currents directly (Allotta et al., 2017; Costanzi et al., 2018). While an augmented model might provide slightly better navigation estimates, the one used in this work is sufficient to accurately compare the outlier filtering methods and further improvements to the prediction phase will be left for future developments.

The vehicle position is then fused with the acoustic measurements, i.e. range $r_{i,j}$ from vehicle i to vehicle j calculated during one network interrogation cycle, and the position of vehicle j encoded in an acoustic message and transmitted from j to i according to the MAC sharing protocol (Munafò and Ferri, 2017). The measurement fusion is done using a classic Extended Kalman Filter (EKF), where the prediction phase is performed using the model (1) and the correction step is done linearising the range equation

$$h(x_i, y_i) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} + \eta_r, \quad (3)$$

where η_r models the noise affecting the range measurements, assumed to be a white, Gaussian random variable with zero mean and covariance R_r. For the purpose of this work, the following simplifications are made in the range measurement evaluation and processing:

- the sound speed is considered to have the constant value of 1500 m/s;
- the delay introduced by the ranging algorithm is neglected.

Despite addressing explicitly these issues in the ranging algorithm might improve the accuracy of the acoustic measurement, an assessment of the impact that these parameters have on the navigation performance goes beyond the scope of this paper.

3. OUTLIERS FILTERING

Acoustic communications might be strongly affected by environmental factors. Intermittent links, strong multipaths are common conditions that result in sporadic and unreliable communications and hence in irregularly time-spaced and potentially wrong localisation fixes. In the case of networked systems, concurrent access to the channel, potential collisions and the relative positioning of the nodes contribute to make these issues worse. Feeding these incorrect measurements to state estimators such as the Kalman filter can significantly disrupt the system performance, causing undesired jumps in the estimation and ultimately the filter divergence. To cope with outliers, the state estimator is thus extended with an additional filtering component which guarantees the consistency of the estimation even in presence of wrong measurements. Online outlier filtering can essentially be carried out following two alternative approaches: pre-filtering outliers before they are used as measurements, or modifying the estimator to make it robust against them. These two approaches are discussed in Sec. 3.1 and Sec. 3.2. At this point, it is worth remarking that the following discussions are meant to present some guidelines on how to address the outlier filtering problem in scenarios similar to the one considered in this work, where outliers affect observations and where the availability of the observations is limited and not predictable.

3.1 Outliers pre-filtering

The first strategy aims at identifying and discarding an outlier before processing the measurement in the state estimator (*pre-filtering*). When some information about the distribution of the measurements noise is known, a new measurement can be classified as an outlier when its statistics belong to a different distribution. A measure of how well the measurements fit with the *a-priori* distribution can be obtained using different metrics. A classic metric well suited to be embedded in Kalman-based estimators for outliers gating is the Mahalanobis distance (Bar-Shalom et al., 2004). A new measurement $z_k \in \mathbb{R}^n$ is accepted as a valid measurement if its normalised innovation (quantified by the Mahalanobis distance) is below a given a threshold T:

$$\sqrt{(z_k - h(\hat{x}_{k+1|k}))^T \mathbf{S}_k^{-1}(z_k - h(\hat{x}_{k+1|k}))} < T. \quad (4)$$

The matrix $\mathbf{S}_k \in \mathbb{R}^{n \times n}$ is the covariance matrix associated to the measurement innovation, defined as:

$$\mathbf{S}_k = \mathbf{H}_k \mathbf{P}_{k+1|k} \mathbf{H}_k^T + \mathbf{R}, \quad (5)$$

where $\mathbf{H}_k$ is the state Jacobian of the output function $h(\cdot)$, and $\mathbf{P}_{k+1|k}$ and $\mathbf{R}$ are the covariance matrices associated with the predicted state $\hat{x}_{k+1|k}$ and the measurement z_k, respectively. In short, this criterion uses the matrix $\mathbf{S}_k$ and the threshold T to define a region of validity V for the innovation. A measurement is considered to be valid (hence not an outlier) if the corresponding innovation

$z_k - h(\hat{x}_{k+1|k})$ falls inside the region V. More specifically, the region of validity V is an ellipsoid centered in the origin whose axes are aligned with the eigenvectors of $\mathbf{S}_k$. The length of each semi-axis is given by the product between the square root of the corresponding eigenvalue of $\mathbf{S}_k$ and the threshold T. The value of the threshold T depends on both the desired confidence level, i.e. the percentage of samples over the entire distribution that should be contained in the region V, and on the dimension n, as stated in Gallego et al. (2013). For instance, in the considered case where the measurement $r_{i,j}$ is uni-dimensional, the value of the threshold associated with a confidence level of 99.7% is 3. An application of this criterion in the underwater domain is shown in Vaganay et al. (1996), where the outliers gating based on the Mahalanobis distance is integrated into a Kalman filtering framework to discard bad acoustic ranges coming from a LBL system. However, due to the high sensitivity to errors in the estimated covariance matrix $\mathbf{S}_k$, this technique can be ineffective in problems where the models are not accurate enough to represent the real system, e.g. due to non Gaussianity of the variables, linearisations or unmodelled dynamics.

In general, online outliers identification methods are prone to failures in the classification of an observation and very sensitive to changes in the choice of the parameters. For these reasons they are best suitable when good measurements are frequent enough to allow the system to recover from deviations given by occasional false positives or false negatives. In the considered case, where measurements are often not frequent and highly spaced in time, a failure in the outlier detection process can be critical for the performance of the navigation system.

3.2 Outlier robust state estimators

A different approach is to design the estimator to be robust to measurement outliers. According to this strategy, the estimator processes all the measurements without attempting to identify outliers. Observations are thus fused with the model-based predictions according to a different cost function with respect to the one used in the classic Kalman filter formulation (De Palma and Indiveri, 2017). The cost function is typically designed to give less confidence to measurement residuals with high norm. The advantage is that outlier filtering is often less sensitive to changes in the filter tuning. This makes outlier robust estimators particularly convenient when the model is not realistic enough to capture all the features of the actual system. Following this approach, a robustification of Kalman-based filters called robustifying recursive Least Squares for Additive Outliers (rLS.AO) is presented in Ruckdeschel et al. (2014). According to the proposed strategy, the update step of the Kalman filter is modified by applying a saturation

$$H_b(x) = x \min\{1, b/\|x\|\}, \qquad (6)$$

defined for some suitable upper bound b and norm (e.g. Euclidean norm), to the correction term $\Delta \hat{x}_k = K_k(z_k - h(\hat{x}_{k+1|k}))$, where K_k is the Kalman gain matrix. No modification is applied to the covariance update part of the filter, since this only provides a minor gain, as stated in Ruckdeschel et al. (2014). Given this, the update step of the Kalman thus simply becomes:
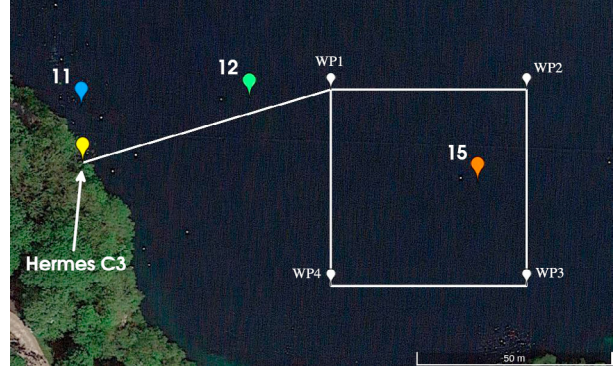

Fig. 2. Experimental setup of the mission held in Vobster Quay, UK on 3rd April 2019.

$$\hat{x}_{k+1|k+1} = \hat{x}_{k+1|k} + H_b(\Delta \hat{x}_k). \qquad (7)$$

When the correction term is lower than the parameter b in norm, the saturation $H_b(x)$ does not affect the output. On the other hand, when $\|\Delta \hat{x}_k\| > b$ the filter will apply a correction with amplitude b along the direction defined by $\Delta \hat{x}_k$, effectively bounding the update performed in the Kalman filter. Comparing with other robustification techniques, the rLS.AO is reasonably simple, non iterative and hence well suited for on-line computation. The bounding threshold b can be thought as a trade-off between the loss of performance with the respect to the classic Kalman-based estimator in the nominal case (i.e. no outliers) and the benefit gained from the added robustness in presence of outliers. In Ruckdeschel et al. (2014) two proposals are provided for the choice of b. In this work, given the state model (1), the value of b has been intuitively chosen to represent the maximum displacement that the filter will allow following a range observation.

4. RESULTS

This section discusses experimental results obtained deploying a network of ecoSUB AUVs integrated with the acoustic network and the navigation filter described in Sec. 2.1. Results are based on multiple experimental campaigns conducted within the Low-Cost AUV Technology (LCAT) project (Fenucci et al., 2018). In the LCAT network setup, the nodes are represented by:

- ecoSUBμ5 AUVs, acting as surface gateways and tasked to station keep around a desired position with a pre-defined tolerance;
- ecoSUBm AUVs, executing predefined missions using the surface gateways as moving LBL anchors;
- *Hermes* Communication, Command and Control (C3) base station. The *Hermes* C3 is typically used to monitor the mission evolution only, but can be configured as an additional surface beacon if needed.

The mission considered in this work took place in Vobster Quay, UK, on 3rd April 2019 during an engineering trial of the system. The experimental setup is shown in Fig. 2. In this specific experiment, the ecoSUBμ5 AUVs (IDs 11, 12 and 15) were tasked to be surface gateways, and physically anchored in three different locations to simulate a station keeping behaviour. One ecoSUBm5 (ID 154) was deployed from the Hermes base station location (Fig. 2, yellow marker) and tasked to travel along a box, a square-shaped
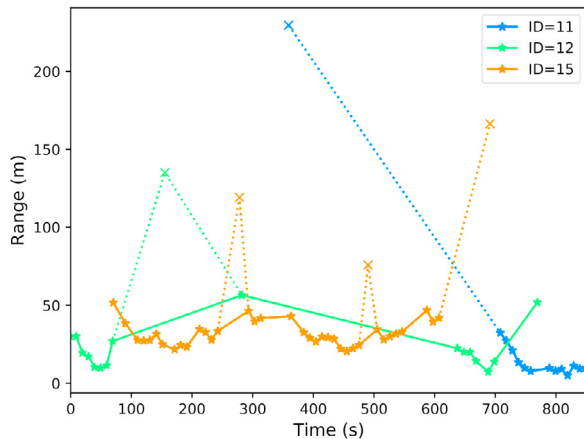
Fig. 3. Acoustic ranges. Ranges evaluated in real time on-board the ecoSUBm5 #154 during the considered mission (stars) are corrupted with a simulated outliers datasets (crosses).

path with a side of approximately 50 m (Fig. 2, while line). Starting from waypoint WP1, the vehicle executed two repetitions of the box in a clockwise sense and then came back to the deployment point for recovery. Range measurements were evaluated on-board the ecoSUBm5 #154 using the Net-LBL algorithm. Access to the acoustic channel was done according to the CSMA protocol, with a minimum inter-transmission delay of 10 s for each network node. The goal of this mission was to collect data to help tuning the filter described in Sec. 2.1. To facilitate the collection of ground truth for the navigational dataset, the ecoSUBm5 #154 had the acoustic modem mounted in the lower part of the hull and facing downwards and tasked to navigate on the surface. In this way, the vehicle could communicate with the other acoustic nodes while having access to the GPS signal. The on-board GPS was hence used for both real-time navigation and as a ground truth in the offline tuning of the filter. Although the quality of the ground truth can be improved, e.g. using a Differential GPS (DGPS), the performance of the GPS receiver installed on the vehicle (Venus 638FLPx GPS receiver, 2.5 m accuracy) is considered sufficient to provide a position reference for the analysis done in this work.

Due to the relative short range between the nodes, and notwithstanding the quite challenging acoustic conditions of the Vobster Quay, only a few outliers were recorded during the mission. For this reason, for the purposes of this work, a sample of 500 outlier-corrupted datasets were generated starting from the range measurements collected on-board the ecoSUBm5 #154 during the mission (Fig. 3, stars). Each dataset contains a random number of wrong observations from each LBL beacon, up to a maximum of 10% of the total number of measurements collected during the mission. Outliers were injected in the original time series consistently with the timing of the experimental setup. This means that, for instance, each synthetic measurement has at least 10 s spacing with respect to the previous and the next range coming from the same LBL anchor, as per the CSMA settings of the deployed network. Outliers were obtained increasing the true range value by a percentage between 50% and 300%,
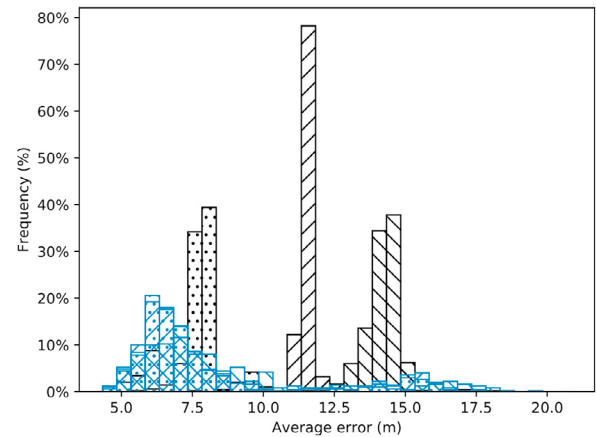

Fig. 4. Average localisation error distribution over the 500 datasets of outliers-corrupted range measurements. The colour identifies the outliers filtering method (black for the Mahalanobis distance gating, blue for the rLS.AO), while the filling patterns (dots, slash e back slash) correspond to the three different sets of tuning parameters for the navigation filter (T1, T2 and T3, respectively).

randomly chosen according to a uniform distribution. This was empirically determined to replicate values consistent with what observed in previous experimental campaigns (Fenucci et al., 2018). Fig. 3 shows an example of a contaminated dataset where the simulated outliers are well evident.

The augmented datasets were then used to perform Monte Carlo simulations and to statistically characterise the AUV navigation performance. Given the model in (1), the performance of the navigation filter is strongly dependent on the choice of the parameters Q_x and Q_y. In fact, the position estimation is as good as the uncertainty introduced in the model by ν_x and ν_y, which represents the effects that environmental disturbances have on the system. Given the variability of the underwater environment, it is difficult to set values for these parameters that are valid in diverse application scenarios. Understanding the sensitivity of the outlier filtering techniques with respect to changes in the navigation filter tuning becomes critical to minimise the tuning itself and to increase the robustness of the system. To this aim, the navigation filter of Sec. 2.1 was modified to use alternatively the outlier pre-filtering based on the Mahalanobis distance, and the rLS.AO method. Both versions of the navigation filter were run on the 500 datasets with three different sets T1, T2 and T3 of values for the parameters Q_x and Q_y. Set T1 was chosen to achieve an empirically good performance for both systems in the given scenario. Sets T2 and T3 were chosen decreasing the variance of Q_x and Q_y by 25% and 50%, respectively, with respect to the baseline. For each run, GPS measurements were only used to initialize the navigation filter. The remaining GPS data are then used to ground truth the navigation performance.

Fig. 4 reports the distribution of the average localisation error over the 500 outlier-contaminated datasets, for both methods and for the three different set of filter parameters. The localisation error is evaluated as the distance between
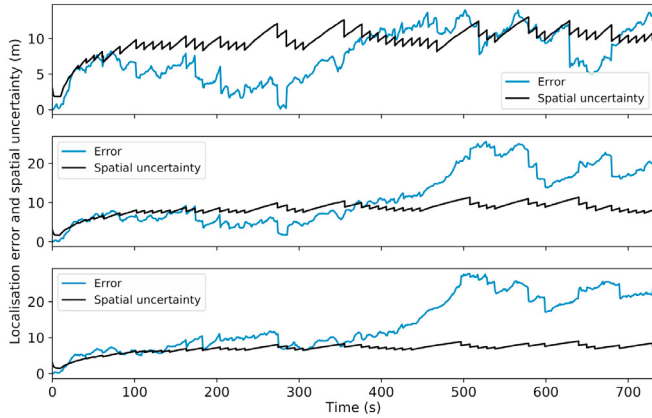
Fig. 5. Navigation error with respect to the GPS vs navigation spatial uncertainty obtained by running the navigation filter with the Mahalanobis distance gating on the dataset in Fig. 3 with the tuning sets T1 (top), T2 (middle) and T3 (bottom).

Fig. 6. Range error distribution evaluated on a set of 550 range measurements.

the position estimated by the navigation filter and the position measured by the GPS at the corresponding time. As it can be noticed, the average error for the rLS.AO method (blue histograms) follows a consistent distribution regardless of the specific filter tuning (the sets of tuning parameters T1, T2 and T3 are represented by different bar-filling patterns – dots, slash and black slash, respectively). Conversely, the outlier pre-filtering based on the Mahalanobis distance (black histograms) proves to be more sensitive with respect to changes in the EKF parameters. Specifically, performance degrades as the filter becomes less accurate in capturing the real estimation uncertainty (e.g. overconfidence). As an example, Fig. 5 shows the comparison between the localisation error (blue line) and the spacial uncertainty of the navigation filter (Webster et al., 2012) (black line) obtained using the Mahalanobis distance gating on the dataset reported in Fig. 3 with the different sets of tuning parameters. The filter starts being overconfident in the navigation solution when the localisation error becomes higher than the estimated uncertainty. It can be noticed how the average localisation error increases as the overconfidence in the estimation is more evident. For instance, using the tuning set T1 the filter is able to correctly capture the localisation error (Fig. 5, top) and this results in a low localisation error (Fig. 4, black, dots-filled histogram). In contrast, the highest average localisation error (Fig. 4, black, back-slash-filled histogram) and the case where the filter starts becoming overconfident right after the initialisation (Fig. 5, bottom), correspond to the tuning set T3. This is due to several causes. Equation (1) aims at representing as Gaussian variables ν_x and ν_y several terms that are intrinsically non-Gaussian (e.g. sea-currents, tidal effects, heading bias, etc.). This means that regardless of how big the filter considers their initial co-variance, the uncertainty introduced in the dynamics will eventually not be able to represent in a realistic manner the actual estimation error. Moreover, the acoustic range measurements are also not Gaussian distributed, hence violating again the EKF assumptions. Fig. 6 shows the distribution of the error between the range measured on-board the vehicle using the network ranging algorithm, and the distance between the GPS positions of the vehicle
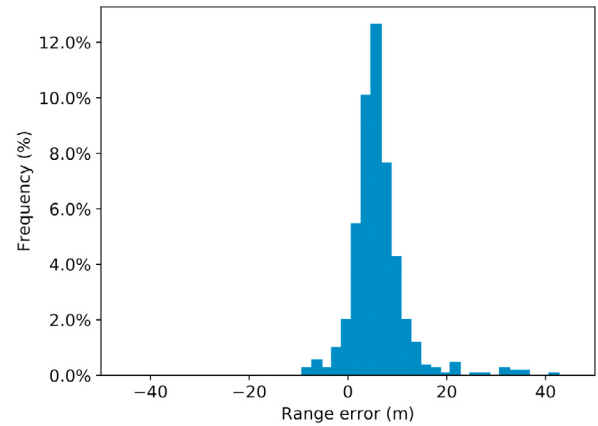
and of the corresponding remote node. The noise affecting the range measurements is not zero mean and almost Gaussian distributed, with the presence of heavy tails due to errors greater than 20 m that are quite likely.

While in different applications and scenarios the two methods might have different performance compared to those presented here, in the considered case the explicit robustness of the rLS.AO outlier filtering method resulted more important to improve the navigation results. Similar results are hence to be expected more in general in typical acoustic environments, where multi-paths are likely to affect the error distributions (Caiti et al., 2013; Fenucci et al., 2018). Having a good EKF tuning is in general a difficult task. In acoustic environments where the distribution of the measurements is difficult to be predicted *a-priori* and susceptible to environmental variations during the mission, having a good filter tuning becomes even more difficult. In these cases, the ability to robustly deal with unexpected measurements of the rLS.AO method can be an important advantage.

5. CONCLUSION

This paper described two methods of outlier detection and filtering aimed at improving performance of AUV navigation. The first method is based on the classic gating based on the Mahalanobis distance-based. In this case, a new measurement is accepted if its normalised innovation is below a given a threshold. The second approach changes the update step of the Kalman filter to make it able to robustly fuse all measurements, including outliers. Results have been based on experimental campaigns done within the LCAT project. Results show that when the distribution of the measurements is difficult to be predicted *a-priori* and susceptible to environmental variations the ability of the rLS.AO method to robustly deal with unexpected measurements can be an important advantage.

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