2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)
Madrid, Spain, October 1-5, 2018

Reliable fusion of black-box estimates of underwater localization

Hendry Ferreira Chame[1], Matheus Machado dos Santos[1], Sílvia Silva da Costa Botelho[1]

***Abstract*— The research on robot tracking has focused on the problem of information fusion from redundant parametric estimations, though the aspect of choosing an adaptive fusion policy, that is computationally efficient, and is able to reduce the impact of un-modeled noise, are still open issues. The objective of this work is to study the problem of underwater robot localization. For this, we have considered a task relying on inertial and geophysical sensory. We propose an heuristic model that performs adaptable fusion of information based on the principle of contextually anticipating the localization signal within an ordered neighborhood, such that a set of nodes properties is related to the task context, and the confidence on individual estimates is evaluated before fusing information. The results obtained show that our model outperforms the Kalman filter and the Augmented Monte Carlo Localization algorithms in the task.**

I. INTRODUCTION

Robot localization in underwater environments is a challenging field of study, with interesting research topics, that includes diverse vehicle configurations, such as the Autonomous Underwater Vehicle (AUV) [1], and the Remotely Operated Vehicle (ROV) [2]. These robots are equipped with a variety of sensory modalities, which provide information on the movement and velocity.

Depending on the sensory technology or data processing algorithms employed, it is normally the case that observations can be compared based on several properties, such as: efficiency, operation rate, reliability, accuracy, availability, or other cost functions. An illustration of this point is the fact that global acoustic positioning sensory are, for instance, subject to intermittence and larger noise levels over short time periods, but estimates do not drift over time, so at the long run measurements can be more reliable than estimates obtained trough onboard dead reckoning [3]. Analogously, the recognition of fixed geo-referenced landmarks can be more informative on the robot position than acoustic global tracking estimates, though the robot may have to surface in order to reduce the localization uncertainty, given that the vehicle cannot receive the global positioning system (GPS) radio frequency in the underwater medium [4].

Data fusion algorithms such as the Kalman filter (KF) family, are very popular in the field. However, by holding the assumption of a Gaussian distribution of noise, the algorithm performs poorly when the estimation process deals with un-modeled noise. Unfortunately, this is likely to happen in dynamic and natural underwater environments, affecting the quality of the obtained estimates. Alternatively, non-parametric algorithms, such as particle filters (e.g. Monte Carlo Localization or MCL [5]), produce multi-modal estimates that can handle un-modeled noise, but are often computationally expensive, and exhibit non-optimal performance in situations close to a Gaussian distribution of measurement noise.

In this paper a neural network model is proposed within a fusion framework, to include knowledge on the relevance of redundant unimodal estimates of the vehicle localization, viewed as black-box computational processes, under particular navigation scenarios. In the model proposed, the nodes' estimates are related to the task context, in order to obtain a more informed fusion process, that is able to be robust to un-modeled noise, at a low computational cost, while aiming to produce close to optimal performance.

The remaining of this document is organized as follows. In Sec. II related works and the motivation behind our proposal is presented. In Sec. III the model proposed is detailed. In Sec. IV the case study is developed by considering the fusion of information from the *ultra-short baseline* (USBL) and the *sound navigation and ranging* (SONAR) sensors, and by comparing the model's performance to the KF and the MCL approach, in relation to the ground truth captured from a *differential global positioning system* (DGPS) setup. Finally, in Sec. V the conclusions and the future perspectives are presented.

II. RELATED WORK AND MOTIVATION

The problem of improving unimodal estimates under non-Gaussian noise has been considered in the literature. One approach that is often taken is to model nonlinearities by augmenting the state representation (e.g. in [6]). When such knowledge is difficult to be obtained, an alternative has been employing supervised learning for correcting the estimates (e.g. in [7]), under the assumption that the task conditions will not vary significantly between the training and the execution phases.

Some works have proposed the fusion of redundant estimations, viewed as black-box processes. Thus, a strategy adopted has been to weight the contribution of each estimate based on the information provided by the error covariance matrix (e.g. inversely proportional weighting [3], or the *covariance intersection* approach in [8]), although in the fusion process correction measurements are implicitly assumed to follow Gaussian distributions.

[1]Universidade Federal do Rio Grande (FURG), Centro de Ciências Computacionais C3, Rio Grande, BRAZIL {hendrychame, matheusmachado, silviacb}@furg.br

978-1-5386-8093-3/18/$31.00 ©2018 IEEE

An alternative approach has been to represent knowledge about the fusion process as a fuzzy rule-based system [9].

Under certain circumstances, in particular with AUVs, acoustic positioning systems can present additional challenges to the sensory fusion algorithm. This is the case, for instance, when data is sent to the robot by modem, and may arrive delayed to the fusion computation. According to [10], methods that handle this condition can be categorized into two groups: those that fuse delayed measurements on arrival (e.g. in [11]), and those that resort to state augmentation to model delays (e.g. in [12]). For the case of ROVs, the umbilical connection to sea surface mitigates the problem of delayed fusion.

Differently from [6] and [7], the model proposed in this work do not include specific knowledge about the task, but heuristically exploits the principle of information anticipation [13]. For this, a neural network framework is designed to model an ordered arrangement between redundant estimations, under the assumption that measurements are received asynchronously but not delayed. Estimations are viewed as black-boxes processes encapsulated within nodes. The nodes' outputs are anticipated by related neighbors, so the confidence on estimates is evaluated within the task context when fusing information, as a means to handle un-modeled noise.

III. THE PROPOSED METHOD

The framework proposed is designed under the principle that several localization algorithms are available to the system under different tasks conditions, so the main goal of the fusion computation is to dynamically consider their relative advantages. Figure 1 illustrates the architecture proposed. A set of sensor measurements in gray boxes are passed to the yellow containers (which encapsulate estimation processes) through the system bus. The blue node includes the fusion algorithm, which fires a reset signal with the available global estimate. Thus, estimators are re-initialized under reliable circumstances. The model's premises are detailed next.

Let an estimator process $i \in I$ provide information at time t on the system's continuous state through the parameters set $\Psi_{i(t)}$, such that

$$\Psi_{i(t)} = \{\mu_{i(t)}, \Sigma_{i(t)}, \sigma_{i(t)}, \delta t_{i(t)}\}, \tag{1}$$

where $\mu_{i(t)}$ is the mean state estimate, $\Sigma_{i(t)}$ is the covariance matrix related to the estimate error, $\sigma_{i(t)}$ is the anticipation limit in standard deviation units, and $\delta t_{i(t)}$ is the time interval between two successive estimations.

Let an ordered arrangement between nodes $i \in I$ be established, based on the following assumptions:

Assumption 1 Nodes $i \in I$ provide redundant information on the system state by encapsulating an estimation process that is unknown to the global fusion policy. Such estimates are assumed to be obtained from nondelayed measurements, and to follow an unimodal distribution, described by a mean value $\mu_{i(t)}$ and uncertainty covariance matrix $\Sigma_{i(t)}$, at time $t \in \mathbb{R}_{\geq 0}$.

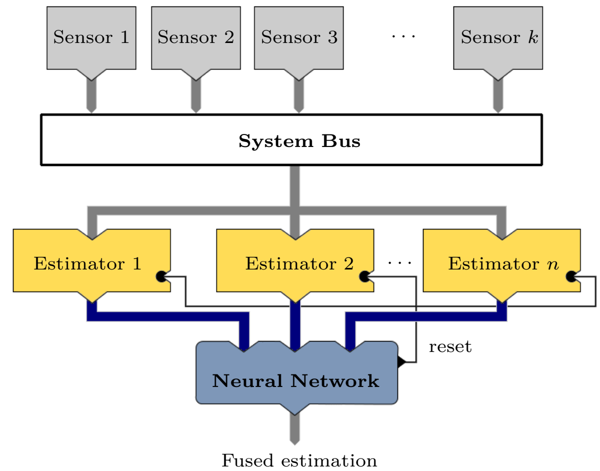

Fig. 1: The fusion architecture proposed.

Assumption 2 An ordering set of functions $f_b(i,t)$ describes the reliability of node $i \in I$, at time $t \in \mathbb{R}_{\geq 0}$, in relation to a behavior profile $b \in B$. A total order is established under the relation less than "$\prec$", such that the following properties are verified:

- Antisymmetry:
  $\forall b \in B, \forall i, j \in I, t \in \mathbb{R}_{\geq 0}$,
  $f_b(i,t) \prec f_b(j,t) \wedge f_b(j,t) \prec f_b(i,t) \Rightarrow i = j$.
- Transitivity:
  $\forall b \in B, \forall i, j, h \in I, t \in \mathbb{R}_{\geq 0}$,
  $f_b(i,t) \prec f_b(j,t) \wedge f_b(j,t) \prec f_b(h,t) \Rightarrow i \prec h$.
- Totality:
  $\forall b \in B, \forall i, j \in I, t \in \mathbb{R}_{\geq 0}$,
  $f_b(i,t) \prec f_b(j,t) \vee f_b(j,t) \prec f_b(i,t) \Rightarrow i \prec j \vee j \prec i$.

In order to model the previous assumptions, let a set of one-dimensional site arrangements $S_b \in S$ represent the relations between process nodes $i \in I$, under a behavior profile $b \in B$. A neighborhood system for S_b can be defined, such that

$$\aleph_{b(t)} = \{\aleph_{bs} | \forall s \in S_b, b \in B\}, \tag{2}$$

where $\aleph_{bs}$ is the set of sites neighboring node s. The sites relationship are subject to the following properties:

i) $s \notin \aleph_{bs}$, that is, a site is not neighboring to itself.
ii) $s \in \aleph_{bg} \Leftrightarrow g \in \aleph_{bs}$, so a neighboring relationship is mutual.

Let $\aleph_{bs}$ be defined by a first-order neighborhood (see Fig. 2), so the clique $c_b = \{s, w\} | s, w \in S_b$. The left and right neighbors of a site s are defined respectively by the functions $c_{lb}(s)$ and $c_{rb}(s)$, such that

$$\begin{aligned} c_{lb}(s) &= g | c_b = \{g, s\}, g \in \aleph_{bs} \\ c_{rb}(s) &= v | c_b = \{s, v\}, v \in \aleph_{bs}. \end{aligned} \tag{3}$$

A. The neural network BAR-F

The structure of the neural network proposed is shown in Fig. 3. At a given instant of time neurons in the

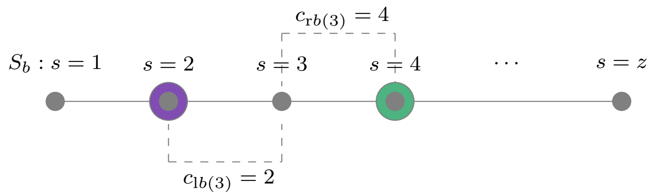

Fig. 2: First-order neighborhood system in a one-dimensional regular site arrangement S_b.

input layers B, A, and R, represent respectively the activation of the behavior profiles (e.g. navigation near the surface, mid-water, sea floor, and so on), the activity (i.e. the availability of a new estimate), and the reliability of the estimators. The output layer F represents the fusion weight assigned to the information provided by individual estimators to the global estimate. Due to the layer structure, the network is named BAR-F. Next, a proposal for the model implementation is detailed.

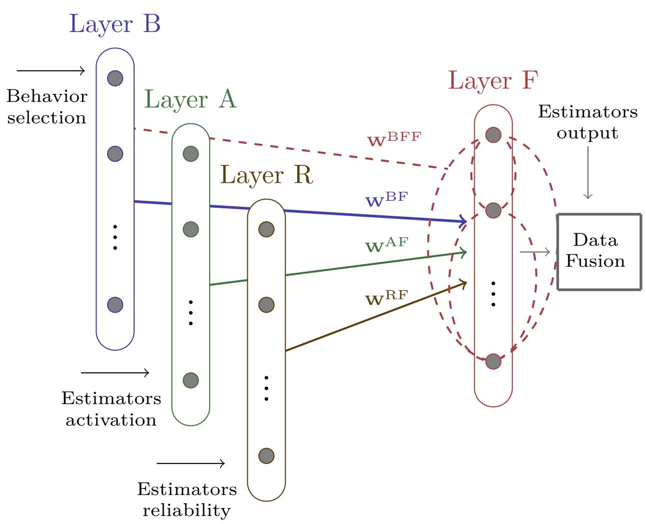

Fig. 3: The neural network BAR-F for data fusion. Circles represent neurons in each layer, and edges represent the connectivity between layers. Layers B, A, R are the inputs and represent respectively: the task behavior profiles, the estimators activation and reliability. Layer F is the output, it represents the weighted contribution to the global estimation. Recurrent connections in layer F model the ordered arrangements within each behavior profile, related to Layer B.

a) Network configuration: Let the positive matrix $\mathbf{W}^{\mathrm{BF}}_{[b\times n]}$ correspond to the parameters given by the system designer, and represent the expected performance of n estimators on each behavior profile b. Let matrix $\mathbf{W}^{\mathrm{AF}}_{[n\times n]}$ be binary diagonal, and represent the predefined availability of estimators (for available nodes $\mathbf{W}^{\mathrm{AF}}_{ii} = 1$, otherwise $\mathbf{W}^{\mathrm{AF}}_{ii} = 0$). Let matrix $\mathbf{W}^{\mathrm{RF}}_{[n\times n]}$ be nonnegative diagonal, and represent previous knowledge on the reliability of estimators (normally set to the identity). Let matrix $\mathbf{W}^{\mathrm{BFF}}_{[b\times n\times n]}$ representing the ordered arrangements of nodes according to the behavior profiles, be modeled analytically by fixing stronger weights to first-order cliques, excitatory weights to left neighbors, and inhibitory weights to right neighbors, so

$$\mathbf{W}^{\mathrm{BFF}}_{bij} = \begin{cases} \left(\mathbf{W}^{\mathrm{BF}}_{bi} - \mathbf{W}^{\mathrm{BF}}_{bj}\right)^{-1} & \text{if } i \neq j \\ 0 & \text{otherwise} \end{cases} . \tag{4}$$

Let the clique functions $c_{\mathrm{lb}}(i)$ and $c_{\mathrm{rb}}(i)$, which allow to query respectively the left and right neighbor of a given node i (see Eq. (3)), be defined based on the information provided by the recurrent connections of layer F, thus

$$\begin{aligned} \breve{c}_{\mathrm{lb}}(i) &= \underset{q=1,\cdots,n}{\arg\max}\ \mathbf{W}^{\mathrm{BFF}}_{biq} \\ \breve{c}_{\mathrm{rb}}(i) &= \underset{j=1,\cdots,n}{\arg\max}\ \mathbf{W}^{\mathrm{BFF}}_{bji} \end{aligned} \tag{5}$$

b) Layers' activation: Let the activation of layer B be defined according to the winner-takes-all policy (i.e. only one behavior is expected to be active at a time), applied to an arbitrary function $f(j,t)$, such that

$$\mathbf{b}_{i(t)} = \begin{cases} 1 & \text{if } i = \underset{b\in B}{\arg\max}\ f(b,t) \\ 0 & \text{otherwise} \end{cases} . \tag{6}$$

Let the activation of neurons in Layers A be defined by

$$\mathbf{a}_{j(t)} = \begin{cases} 1 & \text{if estimator } j \text{ is active} \\ 0 & \text{otherwise} \end{cases} . \tag{7}$$

The information processed by Layer R is determined considering the parameters provided by left neighbors in the hierarchy (as implemented in Eq. (5)). Let the parameter set $\psi_{(t)} = \{\hat{\mu}_{(t)}, \hat{\Sigma}_{(t)}, \hat{\sigma}_{(t)}, \hat{\delta t}_{(t)}\} \in \{\Psi_{1(t)}, \cdots, \Psi_{n(t)}\}$ (see Eq. (1)) for the i^{th} unit be selected, such that

$$\psi_{(t)} = \begin{cases} \Psi_{j(t)} & \text{if } \exists j | j = c_{\mathrm{lb}}(i) \\ \Psi_{i(t)} & \text{otherwise} \end{cases} . \tag{8}$$

Let the activation of Layer R be defined by

$$\mathbf{r}_{i(t)} = h(\gamma_i(t) - \phi_1)\gamma_i(t), \tag{9}$$

so $h(\ )$ is the Heaviside step function, ϕ_1 is a threshold parameter, and $\gamma_i(t)$ is obtained, such that

$$\gamma_i(t) = \frac{1}{1 + \exp(-\phi_2(\hat{\sigma}_{(t)} - f_i(t)))}, \tag{10}$$

where the anticipation delimitation $\hat{\sigma}_{(t)}$ acts like the sigmoid midpoint, and ϕ_2 is the steepness of the curve. The function $f_i(t)$ is defined by

$$f_i(t) = \mathbf{x}^{\top}_{i(t)} \mathbf{V}^{\top}_{i(t)} \mathbf{G}^{-1}_{i(t)} \mathbf{V}_{i(t)} \mathbf{x}_{i(t)}, \tag{11}$$

with $\mathbf{x}_{i(t)} = \mu_{i(t)} - \hat{\mu}_{(t)}$. The matrix $\mathbf{V}_{i(t)}$ corresponds to the $\hat{\Sigma}_{(t)}$ eigenvectors, and $\mathbf{G}_{i(t)} = \hat{\sigma}_{(t)}\mathrm{diag}(\lambda_{(t)})$ is defined from its eigenvalues $\lambda_{(t)}$.

Let the activation of layer F be given by

$$\mathbf{f}_{(t)} = (\mathrm{diag}(\beta)^{-1}\mathbf{b}_{(t)})^\top \Gamma \mathrm{diag}(\mathbf{r}_{(t)}) \tag{12}$$

where $\Gamma = \mathbf{W}^{\mathrm{BF}}\mathbf{W}^{\mathrm{AF}}\mathbf{W}^{\mathrm{RF}}\mathrm{diag}(\mathbf{a}_{(t)})$ and $\beta = \Gamma\mathbf{r}_{(t)}$.

Finally, let the fused system parameters $\bar{\mu}_{(t)}$ and $\bar{\Sigma}_{(t)}$ be obtained by weighting individual estimators' output according to the activation of units in Layer F, thus

$$\begin{aligned} \bar{\mu}_{(t)} &= \mathbf{f}^\top[\mu_1 \cdots \mu_z]^\top \\ \bar{\Sigma}_{(t)} &= [\mathbf{f}_1 \mathrm{I}_d \cdots \mathbf{f}_z \mathrm{I}_d][\Sigma_1 \cdots \Sigma_z]^\top, \end{aligned} \tag{13}$$

where I_d denotes the identity matrix, with d the dimension of the localization task state space.

IV. CASE STUDY

A. The experiment

The experiment was performed in a harbor area of a Yacht Club of Rio Grande, Brazil, with a ROV Seabotix© LBV300-5, equipped with an on-board compass, a Teledyne Blueview© Forward-Looking SONAR P900-130, a Tritech© MicronNav USBL system, and a SOUTH© S82T DGPS. Thanks to a stand-up board fixed on the vehicle (see Fig. 4) the DGPS portable controller remained over the water surface while the vehicle remained underwater, in a constant depth of 0.3 meters, near 3 meters from the seabed.

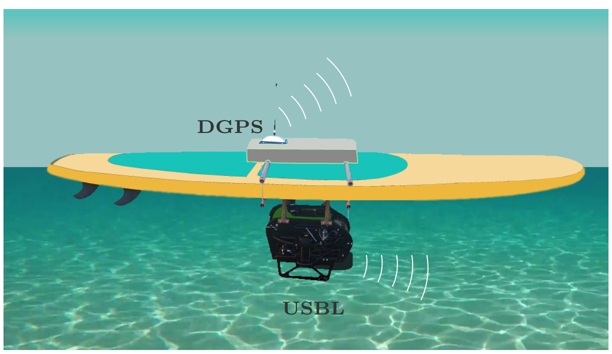

Fig. 4: ROV Seabotix© LBV300-5 fixed to a surfboard.

The vehicle was controlled by a human operator. As shown in Fig. 5, it traveled approximately 693 meters in 61 minutes. The SONAR tilt was about 0º regarding the horizon, its field of view covered a horizontal opening of 130º and a range of 50 meters. In total, it was recorded 19992 grayscale 16-bits images by the SONAR, 3663 heading values by the compass, 3662 positions by the DGPS, and 1450 positions by the USBL. The dataset was processed off-line in GNU Octave version 4.2.1[1].

B. The localization task

The ground truth measurements available corresponded to the geo-referenced Cartesian coordinates of the robot, as registered by the DGPS, thus, the state space representation of the task is

[1]Sources are available at https://github.com/henferch/BAR-F

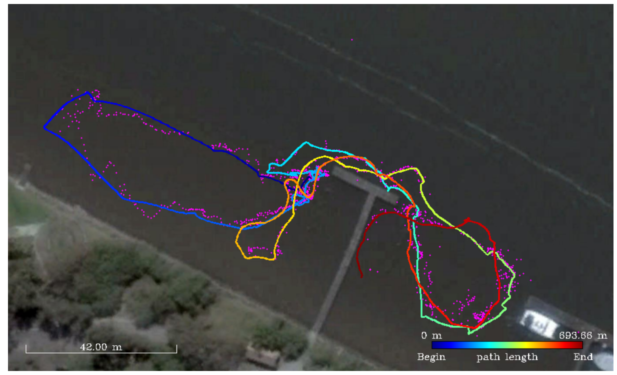

Fig. 5: Traveled path of the vehicle. DGPS readings are shown by the continuous line (colored from blue to red tones). USBL readings are shown by dots in magenta. Map data: Google©, Digital Globe© 09-29-2016, 32° 1' 29.9568" S 52° 6' 24.6096" W.

$$\mathbf{x} = [x\ y]^\top. \tag{14}$$

Only one behavior profile (i.e. navigation near the surface) was considered. Two redundant estimators were implemented, one relying entirely on dead reckoning, whereas the other corresponded to a KF, which included dead reckoning information in the prediction step and USBL measurements in the correction step.

a) Scan-matching motion estimation: The relative motion of the vehicle is estimated from the information provided by the multibeam SONAR, which captures the acoustic beams at once, making the sensor operable in both stationary and moving platforms. The Lucas-Kanade method [14], as implemented in OpenCV version 3.3, was used to perform the scan-matching. The relative change in the robot instantaneous posture between two consecutive acquisitions is estimated from w matching points, by solving the overdetermined system of the form

$$\rho = \left([\mathbf{A}_1 \cdots \mathbf{A}_w]^\top\right)^+ [\mathbf{b}_1 \cdots \mathbf{b}_w]^\top \tag{15}$$

where $(\ )^+$ denotes the Moore–Penrose inverse, and

$$\begin{aligned} \rho &= \begin{bmatrix} \cos(\Delta\theta) & \sin(\Delta\theta) & \Delta x & \Delta y \end{bmatrix}^\top, \\ \mathbf{A}_i &= \begin{bmatrix} x_{i(t-1)} & y_{i(t-1)} & 1 & 0 \\ y_{i(t-1)} & x_{i(t-1)} & 0 & 1 \end{bmatrix}^\top, \\ \mathbf{b}_i &= \begin{bmatrix} x_{i(t)} & y_{i(t)} \end{bmatrix}. \end{aligned} \tag{16}$$

The parameters of interest are the 2D pose of the ROV. That is, the Cartesian displacement Δx, Δy, and the yaw orientation $\Delta\theta$, obtained from ρ.

b) Kalman filter estimation: A classical KF [5] was implemented. The estimated state vector $\mathbf{x}_{(t)}$ is given by

$$\mathbf{x}_{(t)} = \mathbf{F}_{(t)}\mathbf{x}_{(t-1)} + \mathbf{B}_{(t)}\mathbf{u}_{(t)} + \epsilon_{(t)}, \tag{17}$$

where $\mathbf{F}_{(t)}$ is the state transition model, $\mathbf{B}_{(t)}$ is the control input model, $\mathbf{u}_{(t)}$ is the control vector input, and $\epsilon_{(t)}$ is a random Gaussian vector that models the uncertainties introduced by the state transition. The predicted state estimate and covariance are

$$\begin{aligned}\tilde{\mathbf{x}}_{(t|t-1)} &= \mathbf{F}_{(t)}\tilde{\mathbf{x}}_{(t-1|t-1)} + \mathbf{B}_{(t)}\mathbf{u}_{(t)},\\ \tilde{\mathbf{P}}_{(t|t-1)} &= \mathbf{F}_{(t)}\tilde{\mathbf{P}}_{(t-1|t-1)}\mathbf{F}_{(t)}^{\top} + \mathbf{Q}_{(t)}.\end{aligned} \tag{18}$$

The a posteriori state correction is obtained by

$$\begin{aligned}\hat{\mathbf{x}}_{(t|t)} &= \tilde{\mathbf{x}}_{(t|t-1)} + \mathbf{K}_{(t)}\tilde{\mathbf{y}}_{(t)}\\ \hat{\mathbf{P}}_{(t|t)} &= (\mathbf{I} - \mathbf{K}_{(t)}\mathbf{H}_{(t)})\mathbf{P}_{(t|t-1)}\\ \tilde{\mathbf{y}}_{(t)} &= \mathbf{z}_{(t)} - \mathbf{H}_{(t)}\tilde{\mathbf{x}}_{(t|t-1)}\\ \mathbf{S}_{(t)} &= \mathbf{R}_{(t)} + \mathbf{H}_{(t)}\mathbf{P}_{(t|t-1)}\mathbf{H}_{(t)}^{\top}\\ \mathbf{K}_{(t)} &= \mathbf{P}_{(t|t-1)}\mathbf{H}_{(t)}^{\top}\mathbf{S}_{(t)}^{-1}\end{aligned}\quad, \tag{19}$$

where $\mathbf{H}_{(t)}$ is the observation matrix.

Other matrices are set so: $\mathbf{Q}_{(t)} = \text{diag}(\sigma_{\text{odom}})$, $\mathbf{R}_{(t)} = \text{diag}(\sigma_{\text{usbl}})$, $\mathbf{F}_{(t)} = \mathbf{B}_{(t)} = \mathbf{H}_{(t)} = \text{I}$. Data related to the intended motion of the robot was not available, thus, the input $\mathbf{u}_{(t)}$ was taken as the dead reckoning estimate, which is obtained by integrating the estimation of the relative displacement of the robot (from the SONAR scan-matching) along the motion direction, as estimated by the compass sensor. Measurements $\mathbf{z}_{(t)}$ are acquired from the USBL sensor.

C. Results

The model parameters are given in Table I. The estimates by the network BAR-F were compared to: a) dead reckoning (DR), b) the KF algorithm, and c) the Augmented_MCL (A-MCL) particle filter algorithm [5]. The results obtained are shown in Fig. 6. As expected, dead reckoning trajectory drifted over time. KF estimates were severely affected by non-Gaussian noise, notably, when the USBL sensor was not able to provide a reliable measurement and simply returned the relative coordinates of the fixed transceiver. As a multi-modal distribution estimation, A-MCL was able to handle noise running with an 1000-particles population. The BAR-F network was also able to handle noise, but at a much lower computational cost (i.e. complexity $O(nb)$ in the fusion step, for n estimators and b behavior profiles).

P	Estimator 1	Estimator 2	BAR-F
$\mu_{i(0)}$	$\bar{\mu}_{(t)}$	$\bar{\mu}_{(t)}$	-
$\mu_{i(t)}$	$\mu_{1(t-1)} + \mathbf{x}_{\text{sc}(t)}$	$\tilde{\mathbf{x}}_{(t\vert t-1)}$, Eq.(18)	-
$\Sigma_{i(0)}$	diag($[8.0\ 8.0]^{\top}$)	diag($[0.1\ 0.1]^{\top}$)	-
$\Sigma_{i(t)}$	$\Sigma_{1(t-1)} + \text{diag}(\vert\mathbf{x}_{\text{sc}(t)}\vert)$	$\tilde{\mathbf{P}}_{(t\vert t-1)}$, Eq.(18)	-
$\sigma_{i(t)}$	$\sigma_{1(t-1)} + \delta t/(10\theta_3)$	1	-
$\delta t_{i(t)}$	≈ 0.25	≈ 2.50	-
-	$\sigma_{\text{odom}} = [0.5\ 0.5]^{\top}$	$\sigma_{\text{usbl}} = [0.1\ 0.1]^{\top}$	-
ϕ_1	-	-	0.2
ϕ_2	-	-	13.0
$\mathbf{W}^{\text{BF}}$	-	-	$[0.1, 0.9]^{\top}$

TABLE I: Model parameters (P). $\bar{\mu}_{(t)}$ is the global mean issued by the network, $\theta_3 = \text{mean}(\delta t_{2(t)}) = 2.52$. Distances are expressed in m and time in sec. $\mathbf{x}_{\text{sc}(t)} = [\Delta x\ \Delta y]^{\top}$ is the scan-matching motion estimation.

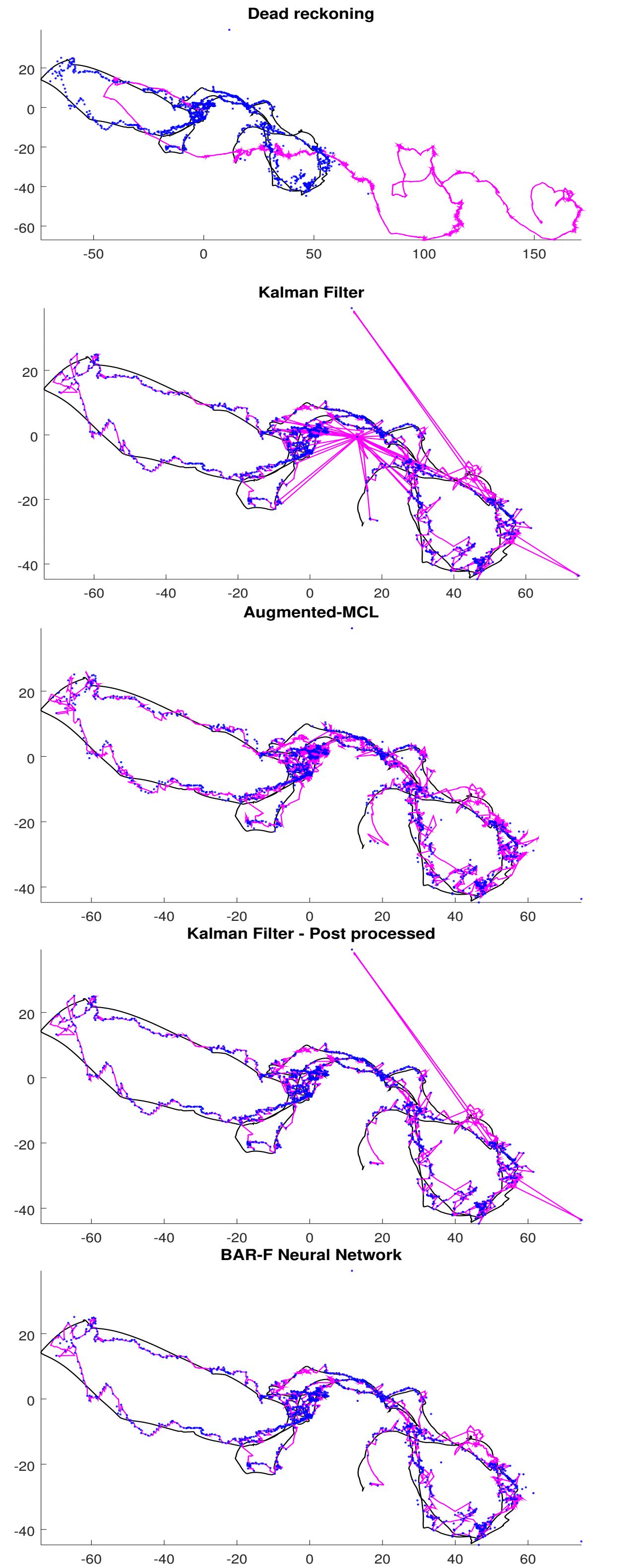

Fig. 6: Relative position in meters to the first reading in *universal transverse mercator* (UTM) coordinates. Estimates (magenta), DGPS (black), USBL (blue).

In order to compare the performance between the algorithms in a close to Gaussian error distribution scenario, data was post-processed to remove potentially invalid

USBL measurements, and given to the KF implementation. The accumulated error in the experiment, relative to the ground truth, is shown in Fig. 7. Table II presents the mean error and standard deviation. As it can be noticed, BAR-F outperformed both KF and A-MCL.

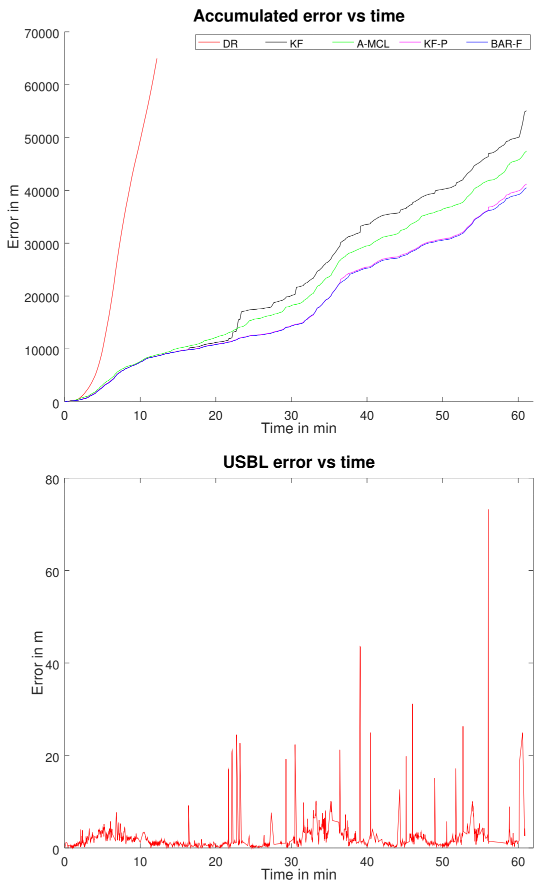

Fig. 7: Top: comparison of the estimation error to the ground truth. Bottom: USBL readings are affected by non-Gaussian noise, but errors do not accumulate.

Algorithm	Mean	Std. Dev.
Dead reckoning	64.7145	38.0802
Kalman Filter	2.7548	4.3562
A-MCL	2.3450	1.8202
Kalman Filter Post-processed	2.0603	2.2855
BAR-F Neural Network	**2.0254**	**1.6539**

TABLE II: Algorithms Comparison, distance in meters.

V. CONCLUSIONS

This work proposed a methodology that allows the system designer to define an ordered arrangement between redundant unimodal estimates of underwater robot localization, within a neural network structure named BAR-F. The framework proposed fuses the available estimates, viewed as black-box processes, by relying on the principle of contextually anticipating the localization signal within a first-order neighborhood, such that estimates are related to the task context, and the confidence on estimates is evaluated previous to the fusion. In the experiment performed the architecture was able to filter unmodeled noise and outperformed KF and A-MCL in a 2D localization task, although the principle can be extended to more complex scenarios. In future works the algorithm is going to be integrated to a bio-inspired localization architecture [15], which is currently under development in our lab.

ACKNOWLEDGMENT

This work has been funded by the National Postdoctoral Program (PNPD), CAPES Foundation, Ministry of Education of Brazil, Brasília - DF 700040-020, Brazil.

REFERENCES

[1] L. Paull, S. Saeedi, M. Seto, and H. Li, “Auv navigation and localization: A review,” *IEEE Journal of Oceanic Engineering*, vol. 39, no. 1, pp. 131–149, Jan 2014.

[2] E. I. Grøtli, J. Tjønnås, J. Azpiazu, A. A. Transeth, and M. Ludvigsen, “Towards more autonomous rov operations: Scalable and modular localization with experiment data,” *IFAC-PapersOnLine*, vol. 49, no. 23, pp. 173 – 180, 2016.

[3] L. Drolet, F. Michaud, and J. Cote, “Adaptable sensor fusion using multiple kalman filters,” in *Proceedings. 2000 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2000)*, vol. 2, 2000, pp. 1434–1439.

[4] R. R. Khan, T. Taher, and F. S. Hover, “Accurate georeferencing method for auvs for oceanographic sampling,” in *OCEANS 2010 MTS/IEEE SEATTLE*, Sept 2010, pp. 1–5.

[5] S. Thrun, W. Burgard, and D. Fox, *Probabilistic Robotics*. Cambridge, Mass.: The MIT Press, Aug. 2005.

[6] M. Morgado, P. Batista, P. Oliveira, and C. Silvestre, “Position usbl/dvl sensor-based navigation filter in the presence of unknown ocean currents,” *Automatica*, vol. 47, no. 12, pp. 2604 – 2614, 2011.

[7] X. Gao, X. Zhong, D. You, and S. Katayama, “Kalman filtering compensated by radial basis function neural network for seam tracking of laser welding,” *IEEE Transactions on Control Systems Technology*, vol. 21, no. 5, pp. 1916–23, 2013.

[8] S. J. Julier and J. K. Uhlmann, “Using covariance intersection for SLAM,” *Robotics and Autonomous Systems*, vol. 55, no. 1, pp. 3 – 20, 2007, simultaneous Localisation and Map Building.

[9] A. Sabra and W. k. Fung, “Dynamic localization plan for underwater mobile sensor nodes using fuzzy decision support system,” in *OCEANS 2017 #8211; Anchorage*, Sept 2017.

[10] A. Gopalakrishnan, N. S. Kaisare, and S. Narasimhan, “Incorporating delayed and infrequent measurements in extended kalman filter based nonlinear state estimation,” *Journal of Process Control*, vol. 21, no. 1, pp. 119 – 129, 2011.

[11] P. Ridao, D. Ribas, E. Hernàndez, and A. Rusu, “Usbl/dvl navigation through delayed position fixes,” in *2011 IEEE International Conference on Robotics and Automation*, May 2011, pp. 2344–2349.

[12] E. Asadi and C. L. Bottasso, “Delayed fusion of relative state measurements by extending stochastic cloning via direct kalman filtering,” in *Proceedings of the 16th International Conference on Information Fusion*, July 2013, pp. 2049–2056.

[13] H. F. Chame and C. Chevallereau, “Grounding humanoid visually guided walking: From action-independent to action-oriented knowledge,” *Information Sciences*, vol. 352-353, pp. 79 – 97, 2016.

[14] B. D. Lucas and T. Kanade, “An iterative image registration technique with an application to stereo vision,” in *Proceedings of the 7th International Joint Conference on Artificial Intelligence - Volume 2*, ser. IJCAI'81, 1981, pp. 674–679.

[15] H. F. Chame, P. L. Drews, and S. S. C. Botelho, “Towards a biologically-inspired model for underwater localization based on sensory-motor coupling,” in *2017 Latin American Robotics Symposium (LARS) and 2017 Brazilian Symposium on Robotics (SBR)*, Nov 2017, pp. 1–6.