Towards Accurate Deep-Sea Localization in Structured Environments based on Perception Quality Cues

Extended Abstract

Arturo Gomez Chavez
Robotics Group, Computer Science & Electrical Engineering,
Jacobs University
Bremen, Germany
a.gomezchavez@jacobs-university.de

Qingwen Xu
School of Information Science and Technology of
ShanghaiTech University
Shanghai, China
xuqw@@shanghaitech.edu.cn

Christian A. Mueller
Robotics Group, Computer Science & Electrical Engineering,
Jacobs University
Bremen, Germany
chr.mueller@jacobs-university.de

Sören Schwertfeger
School of Information Science and Technology of
ShanghaiTech University
Shanghai, China
soerensch@shanghaitech.edu.cn

Andreas Birk
Robotics Group, Computer Science & Electrical Engineering,
Jacobs University
Bremen, Germany
a.birk@jacobs-university.de

ABSTRACT

In recent years, the number of maritime exploration and exploitation activities has rapidly increased, and with it the necessity to perform more complex tasks underwater, e.g., floating manipulation and mapping with Remote Operated Vehicles (ROVs). The first step to perform these activities in a reliable manner, is to obtain an accurate robot localization estimate. Localization approaches based on multi-robot systems or complex acoustic infrastructures have been favored in the literature, but alternatively visual modalities are pursued when these options are not feasible. In this work, we present a two-stage navigation scheme that initially generates a coarse probabilistic map of the workspace that is used to refine localization accuracy and filter noise in the second stage. Additionally, an adaptive decision-making approach is introduced that determines which perception cues to incorporate into the localization filter, i.e., tracked 2D features or plane representations, to ensure high accuracy and reduce computation times. Our approach is thoroughly investigated in simulation and validated with deep-sea field trial data originated from oil & gas commercial operations.

KEYWORDS

Localization; Navigation; Marine robotics; Field robotics; Multimodal perception; Adaptive behavior; Long-term autonomy

ACM Reference Format:
Arturo Gomez Chavez, Qingwen Xu, Christian A. Mueller, Sören Schwertfeger, and Andreas Birk. 2019. Towards Accurate Deep-Sea Localization in Structured Environments based on Perception Quality Cues. In *Proc. of the 18th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2019), Montreal, Canada, May 13–17, 2019*, IFAAMAS, 3 pages.

Proc. of the 18th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2019), N. Agmon, M. E. Taylor, E. Elkind, M. Veloso (eds.), May 13–17, 2019, Montreal, Canada. © 2019 International Foundation for Autonomous Agents and Multiagent Systems (www.ifaamas.org). All rights reserved.

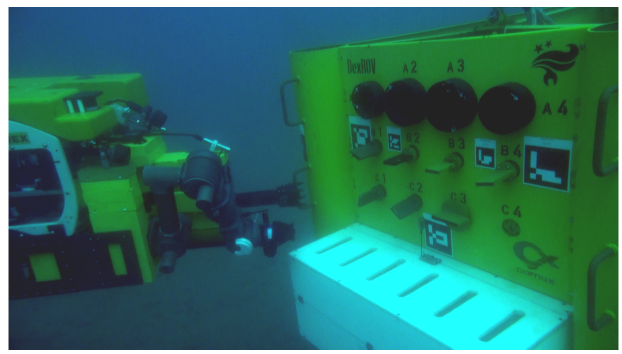

Figure 1: ROV performing oil & gas valve manipulation.

1 INTRODUCTION

In the present work, we propose a navigation scheme that uses visual odometry (VO) methods based on stereo camera imagery [5] and an initial probabilistic map of the working space to boost localization accuracy in challenging conditions. As an example, we use the EU-DexROV project [1, 2, 4] in which the final objective is the monitoring and dexterous manipulation of an oil & gas panel (Fig. 1). However, the nature of underwater scenarios where the light behavior produces low contrast, blurred and color attenuated images highly impacts the performance of VO approaches.

To solve this, we combine plane registration and feature tracking methods to obtain odometry values. 3D planes are extracted from dense point cloud (DPC) generators which produce complete disparity maps at the cost of depth accuracy, but their density is key to find reliable 3D planes. This is useful in structured environments which predominantly contain planar surfaces that can be represented as plane primitives to reduce localization drift. Likewise, a decision-making strategy based on image quality is used to select which visual odometry method to perform in order to obtain more reliable measurements and improve computation times.

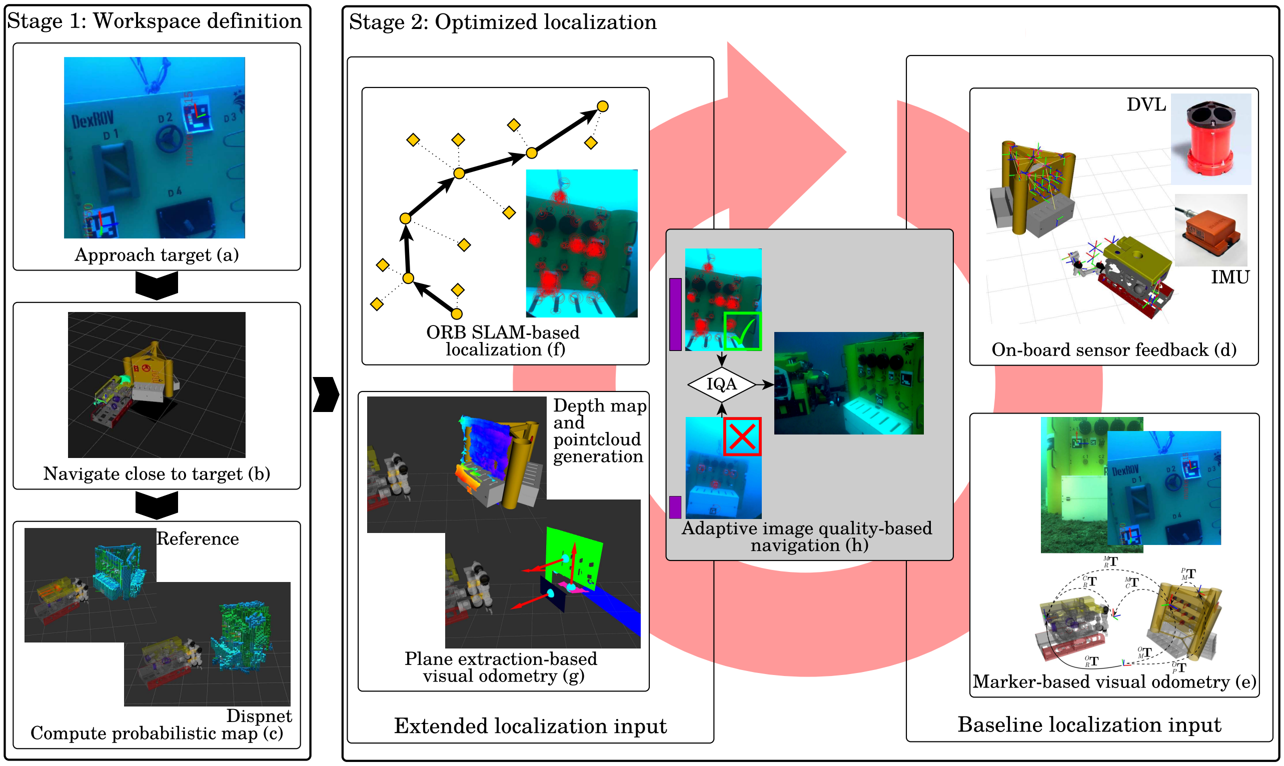

Figure 2: Illustration of the proposed two-stage navigation scheme – from Workspace definition to optimized localization. First stage: (a) recognize the target and compute its pose based on visual markers, (b) navigate close to the target based on navigational sensors and visual markers, (c) generate probabilistic with stereo imagery and Dispnet [3]; RGB-D camera based probabilistic map displayed for reference. Second stage: (f)-(h) show multimodal localization inputs which are incorporated to a final Kalman filter-based localization estimate. An image quality assessment (IQA) [6] is introduced (h) to validate reliability of the extended localization inputs to boost the accuracy of the estimates given by the baseline inputs.

2 METHODOLOGY

Figure 2 illustrates the proposed two-stage navigation scheme:

First stage-*Workspace definition with loose localization*

1.1. Approach the target until its global 3D pose its determined with confidence based on a priori knowledge; see Fig. 2(a).
1.2. Navigate using odometry from navigation sensors and visual landmarks (*baseline localization*); see Fig. 2(a)(b).
1.3. Compute a probabilistic map from stereo input of the target while navigating based on the odometry uncertainty; see examples in Fig. 2(c).

Second stage-*Optimized localization*

2.1 Evaluate the quality and reliability of the visual input, i.e., stereo imagery, based on image quality measures (Fig. 2(h)) and determine which of the next VO modalities to use to extend the localization inputs:
2.2.a Extract planes [8] from dense point clouds [3], filtered using the probabilistic map computed in the first stage to avoid huge drifts and noise artifacts as shown in Fig. 2(g).
2.2.b Extract/track 2D features from imagery; see Fig. 2(f).
2.3. Compute VO either from plane registration [7] or feature tracking [5] depending on the image quality assessment (IQA) [6] and integrate the results into the localization filter.

3 EXPERIMENTAL RESULTS

Using the IQA to decide which VO inputs to integrate into the localization filter (EKF-adaptive) reduces the pose error and increases the smoothness of the followed trajectory. Simply integrating all odometry inputs (EKF-all) does not boost performance as the kalman filter does not reason about the quality of the sensor data except for examining the inputs covariance matrix, see Table 1(b). Table 1(a) shows the higher computational costs of the plane-based VO.

Table 1: Image quality based navigation performance

	VO-ORB	VO-planes
CPU [%]	3.2	6.8
GPU [%]	0.1	17.6
Time [s]	0.145	3.151

(a) Computation performance

	EKF-all	EKF-adpative
Translation ϵ[m]	0.73 ± 0.38	0.61 ± 0.14
Orientation ϵ[deg]	8.93 ± 4.22	3.02 ± 1.06
Autocorrelation (Smoothness)	0.92	0.95

(b) Pose error and trajectory autocorrelation [4]

REFERENCES

[1] A. Birk, T. Doernbach, C. Mueller, T. ÅĄuczynski, A. Gomez Chavez, D. Koehntopp, A. Kupcsik, S. Calinon, A. K. Tanwani, G. Antonelli, P. Di Lillo, E. Simetti, G. Casalino, G. Indiveri, L. Ostuni, A. Turetta, A. Caffaz, P. Weiss, T. Gobert, B. Chemisky, J. Gancet, T. Siedel, S. Govindaraj, X. Martinez, and P. Letier. 2018. Dexterous Underwater Manipulation from Onshore Locations: Streamlining Efficiencies for Remotely Operated Underwater Vehicles. *IEEE Robotics Automation Magazine* 25 (Dec 2018).

[2] Jeremi Gancet, Peter Weiss, Gianluca Antonelli, Max Pfingsthorn, Sylvain Calinon, Alessio Turetta, Cees Walen, Diego Urbina, Shashank Govindaraj, Pierre Letier, Xavier Martinez, Joseph Salini, Bertrand Chemisky, Giovanni Indiveri, Giuseppe Casalino, Paolo di Lillo, Enrico Simetti, Daniela de Palma, Andreas Birk, Tobias Fromm, Christian Mueller, Ajay Tanwani, Ioannis Havoutis, Andrea Caffaz, and Lisa Guilpain. 2016. Dexterous Undersea Interventions with Far Distance Onshore Supervision: the DexROV Project. In *IFAC Conference on Control Applications in Marine Systems*.

[3] N. Mayer, E. Ilg, P. Häusser, P. Fischer, D. Cremers, A. Dosovitskiy, and T. Brox. 2016. A Large Dataset to Train Convolutional Networks for Disparity, Optical Flow, and Scene Flow Estimation. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 4040–4048.

[4] Christian A. Mueller, Tobias Doernbach, Arturo Gomez Chavez, Daniel Koehntopp, and Andreas Birk. 2018. Robust Continuous System Integration for Critical Deep-Sea Robot Operations Using Knowledge-Enabled Simulation in the Loop. In *International Conference on Intelligent Robots and Systems*.

[5] Raul Mur-Artal and Juan D Tardós. 2017. Orb-slam2: An open-source slam system for monocular, stereo, and rgb-d cameras. *IEEE Transactions on Robotics* 33, 5 (2017), 1255–1262.

[6] H. Ziaei Nafchi and M. Cheriet. 2018. Efficient No-Reference Quality Assessment and Classification Model for Contrast Distorted Images. *IEEE Transactions on Broadcasting* 64, 2 (June 2018), 518–523.

[7] Kaustubh Pathak, Andreas Birk, Narunas Vaskevicius, and Jann Poppinga. 2010. Fast registration based on noisy planes with unknown correspondences for 3-D mapping. *IEEE Transactions on Robotics* 26, 3 (2010), 424–441.

[8] Jann Poppinga, Narunas Vaskevicius, Andreas Birk, and Kaustubh Pathak. 2008. Fast plane detection and polygonalization in noisy 3D range images. In *Intelligent Robots and Systems, 2008. IROS 2008. IEEE/RSJ International Conference on*. IEEE, 3378–3383.