Master Thesis - Internship Report

Maria Luiza COSTA VIANNA - CI2019 - ROB

Real-time vision-aided inertial odometry for an AUV

Internship at **FORSSEA ROBOTICS**
Paris - France

Company Supervisor:
Jéremy NICOLA, Robotics Engineer at Forssea Robotics
Professor Supervisor:
Luc JAULIN, Professor in Robotics at Ensta Bretagne

Abstract

This work details the development of a positioning system that couples computer vision and inertial navigation with the objective of estimating deviation during station keep in underwater environments. This combination of sensors was made since Global Navigation Satellite Systems (GNSS) are not available underwater.

Visual information is acquired by NAV CAM, a camera produced and designed by Forssea Robotics. NAV CAM is able to detect a known pattern and determine its pose with respect to the pattern coordinate frame. The inertial navigation information was obtained using an Inertial Measurement Unit (IMU) equipped with both a 3D accelerometer and gyroscope, embedded on NAV CAM.

In this work, different available methods for visual-inertial odometry were studied and our system was developed using an already existent solution as a base. However, since most part of available systems are not developed having in mind the underwater environment, the main contribution of this work was to adapt the existent solutions to our context and needs.

Keywords: Localization, Extended Kalman Filter, Computer Vision, Underwater Navigation

Résumé

Ce travail détaille le développement d'un système de positionnement qui associe vision par ordinateur et navigation inertielle. Le but étant d'estimer la déviation d'un système pendant une mission de station keep dans l'environnement sous-marin. Cette combinaison de capteurs a été adoptée étant donné que les systèmes de navigation par satellite ne sont pas disponibles dans cet environnement.

Les données visuelles sont acquises par NAV CAM, une caméra produite et conçue par Forssea Robotics. NAV CAM est capable de détecter un motif connu et de déterminer sa position et orientation par rapport au repère de coordonnées du motif. Les informations de navigation inertielle ont été obtenues à l'aide d'une IMU équipée d'un accéléromètre et d'un gyroscope 3D, embarquée sur NAV CAM.

Dans ce travail, différentes méthodes disponibles pour l'odométrie visuelle-inertielle ont été étudiées et notre système a été développé en utilisant une solution déjà existante comme base. Cependant, comme la plupart des systèmes disponibles ne sont pas développés en tenant compte l'environnement sous-marin, la principale contribution de ce travail a été d'adapter les solutions existantes à notre contexte et à nos besoins.

Mots-clés : Localisation, Filtre de Kalman Étendu, Vision par Ordinateur, Navigation Sous-Marine

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Introduction

1.1 Forssea Robotics

Forssea Robotics is a start-up founded in April 2016 at École Polytechnic by Gautier Dreyfus and Maxime Cerramon . It was created with the objective of cutting down operating costs in the offshore energy markets, bringing new subsea tools to operators. Today, employees are split between the company's headquarters in the XV^{th} district of Paris, where the research and development(R&D) team is located and the company's workshop, where tests take place, located in Frontignan.

Considering the actual context, where underwater operations are extremely expensive (a connection to an underwater installation costing around 100k euros per day), Forssea's first project is developed. ATOLL, a ROV that can perform a fully autonomous approach and docking based on embedded control algorithms. Once the link is obtained to the seabed target, ATOLL can either transfer power and data, or mechanically engage the target for recovery back to surface and valve manipulation. The advantage is that the tonnage of carriers is reduced, since ATOLL is a small robot that can be deployed from small ships. In addition, its autonomous navigation reduces the human factor and the time of operation.

Another ROV produced by Forssea is ARGOS. ARGOS is compact in design and is primarily suited to inspection and light intervention tasks. The vehicle is powerful enough to perform maintenance and repair duties. Both ROVs can achieve 2000m depths.

Forssea produces autonomous systems. For this the ROVs produced on the company have multiple sensors embedded, including visual sensors, also developed by Forssea. Today, four cameras are produced.

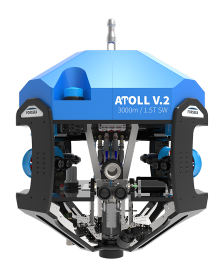
- SMART CAM is a fixed focus High Definition Camera adapted for advanced subsea vision applications. The camera is ideal to equip ROV/AUV for underwater photogrammetry or stereo embedded vision .

- OBS CAM is a camera that provides HD video streaming over Ethernet at the lowest bandwidth, latency and power. It is ideally suited for low and black light applications. It is a perfect fit for inspection and remote monitoring applications.

- NAV CAM is a ROV/AUV visual based navigation and control center. It features a Jetson TX2 board, a pressure sensor and an Inertial Measurement Unit (IMU). Currently, image treatment is processed in real-time using dedicated software to achieve highly accurate positioning.

- POLAR-X is Forssea Robotics patented development in real-time subsea enhanced vision where a Smart Camera is used with polarized lights and real-time embedded software to reduce back scattering effect of turbidity.

(a) ARGOS - Hybrid Light-Intervention Smart ROV



(b) Atoll

Figure 1.1 – AGOS and ATOLL

In 2019, FORSSEA announced new collaborations with DEEPOCEAN to develop autonomous underwater ROV systems and with STR to deploy visual positioning technology worldwide.

1.2 Objectives

Localization in underwater environments can be a real challenge, due especially to the fact that Global Navigation Satellite System (GNSS) information, interpreted as electromagnetic waves, is not available. In this context, currently, most part of underwater systems use acoustic positioning techniques, that consist of systems composed by transmitter and receivers of acoustic waves. These systems are usually classified into three categories, Long Baseline (LBL), Ultra-Short Baseline (USBL) and Short Baseline(SBL).

- LBL
  Using a LBL system we can estimate position within a confined area. Transponders are positioned on the seabed and for each transponder an absolute position is established. A robot with an embedded transceiver (transmitter and receiver) sends a signal that is received by transponders. The transponders reply and the replies are received by the transceiver. With time delays and information about the transponders we can deduce an absolute position for the target.

- SBL
  These systems are similar to LBL systems. The difference is that instead of having transponders mounted on the seabed, the system will have transceivers mounted on the bottom of a ship. This allows a wider locomotion and it is easier to install and calibrate. The target has a transponder embedded. One of the transceivers sends an acoustic wave that is received by the transponder, that responds. Then its message is received by all the transceivers on the ship. With the information about the duration from the initial transmission until the detection of a reply, we can estimate the relative position of the robot to the ship. The precision of this method is related to the distance between transceivers, that is made large as practical given physical space limitations.

- USBL
  Like SBL systems, USBL does not need to have components installed on the seabed. The difference to SBL is that only one transceiver is installed on the ship's bottom.

The presented solutions for underwater localization present high accuracy, however they imply that the system will always have a ship or the seabed by their side in order to be able of estimating its position. In this context, another technique is applied when more autonomy is required, an Inertial Navigation System(INS) aided by a Doppler Velocity Logger(DVL).

A DVL is an acoustic sensor that estimates velocity relative to the sea bottom. It is composed by transceivers that send acoustic signals in different directions. These signals are reflected on the seabed and received by the transceiver. The period between the sending and the reception of these acoustic pulses are used to estimate the sensor's speed converted into an XYZ coordinate frame.

The disadvantages is that DVLs are extremely expensive, it will cost at least 20 thousands euros. In addition, it does not work under all the circumstances since it is highly affected by noise and by other DVLs present on the environment.

At Forssea, the objective is to create a robust vision based underwater locator, considering that a camera is not an expensive complement and it does not disturb the environment. In this context, biodegradable and anti marine-growth markers are used, figure 1.2. They are previously placed in known positions and vision algorithms, developed in the company, allow the detection of these markers and calculate the position of the camera with respect to them.

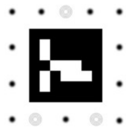


FIGURE 1.2 – Marker

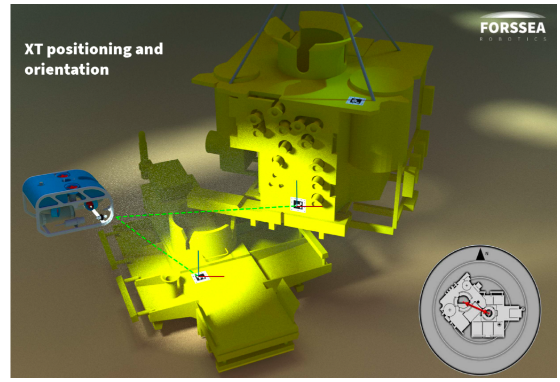


FIGURE 1.3 – Autonomous underwater localization using markers

In order to increase the robustness of this technique, today they need to be capable of automatically stabilizing the robot/camera in front of the marker regardless of the system's deviation in underwater environment. A perturbation may engender a complete loss of the marker from the field of vision. This would lead to the robot drifting due to the absence of exteroceptive information.

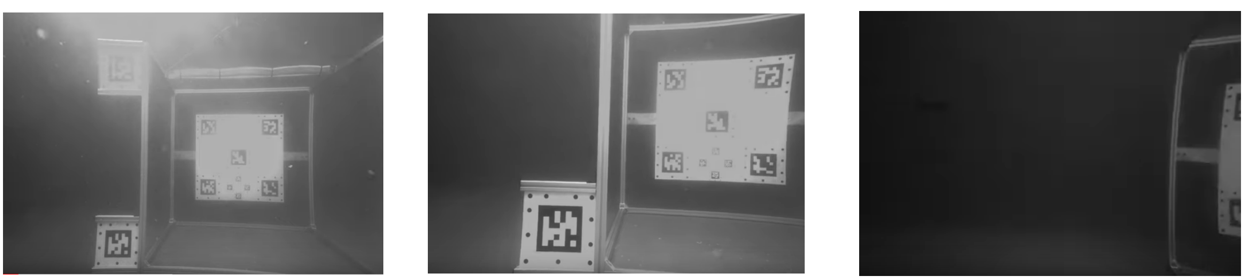


FIGURE 1.4 – Loss of the marker from the field of visioin during station keep

In this context, my internship objectives were defined. By estimating the position and displacement of the robot through a sensor fusion algorithm, I should be capable of estimating deviation and use this information to stabilize it in front of the marker. The idea was to develop an algorithm that would run in real time in NAVCAM.

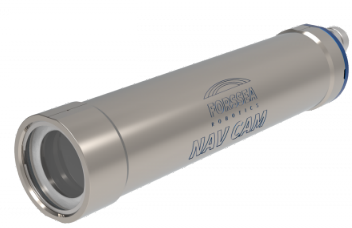


FIGURE 1.5 – NAVCAM

Conclusion and Recommendations

2.1 Conclusions

The main objective of this dissertation is to determine deviations during station keep through position estimation by merging data from a camera and an IMU with an Extended Kalman Filter algorithm. Visual aiding consists of feature's pixel positions and is acquired by Nav Cam. The background knowledge required to accomplish this task is developed throughout the early chapters. Chapter 5 presents with details the algorithm used and chapter 6 its implementation on our system. Then, in chapter 7, hardware configuration and different tests are presented, from which the following conclusions are inferred :

- For having odometry estimation in real time, the camera acquisition rate may not be superior to 15 Hz. Otherwise, our algorithm can not treat all the arriving information. The recommended IMU rate is 100 Hz.
- The system is accurate for small displacements, around 15 meters. It presented an accuracy around 10 centimeters.
- For missions with big displacements, it can still be precise if the target's movement is composed in majority by translations instead of rotations.
- For missions with big displacements the error obtained was within the marge of 70 centimeters. This value is no longer acceptable for station keep purposes.
- Non-static features affect negatively the system's estimation only when they are the majority on the field of vision. In this context, in the underwater environment, the closer we are placed to the marker, the less we will be affected by moving particles in the water.
- System's precision is directly proportional to the number of tracked features per frame, and not by the number of frames per second.
- Zero velocity update allowed us to stabilize the system during stand still periods by maintaining small covariance values.
- Treatment of estimated 3D position of features during small movement periods allowed us to stabilize the system by maintaining small covariance values.

2.2 Recommendations for Further Research

- The next step of this work would be to test the developed algorithm in an underwater context during a stand still mission.
- In order to augment the precision of the algorithm is recommended to use the camera's pose with respect to the marker's coordinate frame, determined by Nav Cam, to update the estimation.

Bibliographie

[1] Anastasios I. Mourikis and Stergios I. Roumeliotis
A Multi-State Constraint Kalman Filter for Vision-aided Inertial Navigation.
Proceedings 2007 IEEE International Conference on Robotics and Automation,2007.

[2] Joshi, Rahman, Kalaitzakis, Cain, Johnson, Xanthidis,Karapetyan, Hernandez, Quattrini Li, Vitzilaios and Rekleitis
Experimental Comparison of Open Source Visual-Inertial-Based StateEstimation Algorithms in the Underwater Domain.
Cornell University,2019.

[3] C. Forster, Z. Zhang, M. Gassner, M. Werlberger, and D. Scaramuzza
SVO : Semidirect visual odometry for monocular and multicamera systems.
IEEE Trans. Robot., vol. 33, no. 2, pp. 249–265, 2017.

[4] S. Lynen, M. Achtelik, S. Weiss, M. Chli, and R. Siegwart
A robust and modular multi-sensor fusion approach applied to MAV navigation.
IROS, 2013

[5] M. Bloesch, M. Burri, S. Omari, M. Hutter, and R. Siegwart
Iterated extended Kalman filter based visual-inertial odometry using direct photometric feedback.
Int. J. Robot. Res., vol. 36, pp. 1053–1072, 2017.

[6] Y. Lin, F. Gao, T. Qin, W. Gao, T. Liu, W. Wu, Z. Yang, and S. Shen
Autonomous aerial navigation using monocular visual- inertial fusion.
J. Field Robot., vol. 00, pp. 1–29, 2017.

[7] J. Delmerico and D. Scaramuzza
A Benchmark Comparison of Monocular Visual-Inertial Odometry Algorithms for Flying Robots.
J. Field Robot., vol. 00, pp. 1–29, 2017.

[8] Gary Bradski and Adrian Kaehler. *Learning OpenCV*. O'Reilly Media,First Edition,2008.

[9] David H. Titterton et John L. Weston. *Strapdown Inertial Navigation Technology - 2nd Edition*. The Institution of Electrical Engineers, 2004.

[10] Katsuhiko Ogata. *Modern Control Engineering.*. Pearson, 2009.

[11] Luc Jaulin. *La Robotique Mobile*. ISTE,2015.

[12] Burri, Michael and Nikolic, Janosch and Gohl, Pascal and Schneider, Thomas and Rehder, Joern and Omari, Sammy and Achtelik, Markus W and Siegwart, Roland.
The EuRoC micro aerial vehicle datasets.
The International Journal of Robotics Research,2016.

[13] Ferrera, Maxime and Moras, Julien and Trouvé-Peloux, Pauline and Creuze, Vincent and Dégez, Denis.
The Aqualoc Dataset : Towards Real-Time Underwater Localization from a Visual-Inertial-Pressure Acquisition System.
TIROS Workshop - New Horizons for Underwater Intervention Missions : from Current Technologies to Future Applications,2018.

[14] Mouats T., Aouf N., Vidas S.
Performance Evaluation of Feature Detectors and Descriptors Beyondthe Visible.
Journal of Intelligent and Robotic Systems (2018) 92 :33–63,2017.

[15] BOYRAZ p., BAYRAKTAR E.
Analysis of Feature Detector and Descriptor Combinations with a Localization Experiment for Various Performance Metrics.
Turkish Journal of Electrical Engineering and Computer Sciences, (2017) .

[16] Wan W., Peng M.,Xing Y. and Wang Y.
A Performance Comparison of Feature Detection for Planetary Rover Mapping and Localization.
The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLII-3/W1, 201, 2017 .

[17] Maxime Ferrera, Julien Moras, Pauline Trouvé-Peloux and Vincent Creuze
Real-Time Monocular Visual Odometry for Turbid and Dynamic Underwater Environments.

[18] Chris Harris and Mike Stephens
A COMBINED CORNER AND EDGE DETECTOR.
The Plessey Company pic. ,1988

[19] Shi J., Tomasi C.
Good Features to Track.
IEEE Conference on Computer Vision and Pattern Recognition (CVPR94),1994

[20] Rosten, Edward ; Tom Drummond
Fusing points and lines for high performance tracking.
IEEE International Conference on Computer Vision. 2. pp. 1508–1511.,2005

[21] David G. Low
Distinctive Image Featuresfrom Scale-Invariant Keypoints.
University of British Columbi,2004

[22] Herbert Bay, Andreas Ess, Tinne Tuytelaars, and Luc Van Gool
Speeded Up Robust Features.
ETH Zurich, Katholieke Universiteit Leuven,2006

[23] Chapter 14, Motion Analysis Optical flow
http ://user.engineering.uiowa.edu/ dip/LECTURE/Motion2.html
Accessed on July,2019

[24] Martin A. Fischler and Robert C. Bolles
Random Sample Consensus : A Paradigm for Model Fitting with Applications to Image Analysis and Automated Cartography
Comm. ACM. 24 (6) : 381–395. doi :10.1145/358669.358692. June 1981.

[25] David A. Forsyth and Jean Ponce
Computer Vision, a modern approach. Prentice Hall.
ISBN 978-0-13-085198-7, 2003.

[26] D. C. Brown
Decentering Distortion of Lenses.
Photometric Engineering 32(3)(1966), 444–462.

[27] Jay A. Farrell.
Aided Navigation - GPS with High Rate Sensors.
The McGraw-Hill Companies, 2008.

[28] A. B. Chatfield.
Fundamentals of High Accuracy Inertial Navigation.
Reston, VA : AIAA, 1997.

[29] Gilbert Strang.
Linear Algebra and its Application.
Student edition, Thomson Learning, 2016.

[30] D. Nistér.
An efficient solution to the five-point relative pose problem.
IEEE transactions on pattern analysis and machine intelligence, vol. 26, no. 6, pp. 756–770, 2004.

[31] V. Lepetit, F. Moreno-Noguer, and P. Fua.
Epnp : An accurate o (n) solution to the pnp problem.
International journal of computer vision, vol. 81, no. 2, pp. 155–166, 2009.

[32] Eun-Hwan Shin.
Estimation techniques for low-cost inertial navigation.
UCGE report, 20219, 2005.