Application of Terrain Based Navigation and Scan Matching to Mine Countermeasures

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Abstract

In the Mine Countermeasures (MCM) context, the use of robotic underwater platforms is increasing. However, some constraints are inherently linked with Mine Countermeasures (MCM) such as the necessity of covert operations or the potential lack of knowledge of the working area. Those constraints can make the navigation of robotic platforms harder. Moreover, MCM is phase based since it is defined around a set of stages including detection, classification, identification and neutralisation. At the moment, used platforms are specialized in a peculiar phase. As a result, a reacquisition of the target must be done between each phase by different robots. Due to those reacquisition, the mission performance is directly dependent on the accuracy of the navigation and pose estimation.

In the following report, two methods aimed at improving the robot navigation will be dealt with: Terrain Based Navigation (TBN) and Scan Matching. Both methods are feature based. Contrary to the former method which needs an a priori knowledge of the environment, the latter uses two successive overlapping measures to compute a local fix. The aim of this report is to determine to what extend the a priori knowledge can be degraded for the Terrain Based Navigation (TBN) and what is the minimum overlapping percentage of successive measure for Scan Matching to be able to provide a fix. In addition, the confidence of the methods will be analyzed.

Résumé

Dans un contexte de guerre des mines, l'utilisation de plateformes sous-marines autonomes est de plus en plus commun. Or, certaines contraintes inhérentes à la guerre des mines comme l'impossibilité de faire surface ou le peu de connaissances des zones d'emploi peuvent compliquer la localisation de ces robots. Qui plus est, la guerre des mines est généralement divisée en trois phases (détection, identification et neutralisation) alors que les plateformes utilisées sont spécialisées uniquement pour l'une de ces phases. En conséquence, une réacquisition de la cible est effectuée entre chaque phase. De ce fait, la précision de la navigation est un facteur déterminant pour la réussite des opérations de déminage.

Dans ce rapport, deux méthodes d'amélioration de la localisation seront donc considérées : le Terrain Based Navigation (TBN) et le Scan Matching. Ces deux méthodes sont basées sur la corrélation de caractéristiques localement uniques. La première nécessite des connaissances à priori de l'environnement tandis que la seconde tente de trouver des similitudes dans le chevauchement de deux mesures successives. Le but de l'analyse à venir est de déterminer dans quelle mesure la carte à priori peut être détériorer dans le cas de la Terrain Based Navigation (TBN), et du pourcentage de chevauchement minimal pour le Scan Matching. De plus, nous tacherons également de fournir une métrique permettant d'attribuer une confiance aux résultats.

Contents

Introduction 5

1 Context of the internship 7
- 1.1 Research centre . . . 7
- 1.2 Mine Countermeasures . . . 8

2 Underwater navigation 9
- 2.1 Dead Reckoning . . . 9
- 2.2 Underwater Acoustic Positioning Systems . . . 10
- 2.3 Inertial Navigation System . . . 11
- 2.4 Through-the-sensor methods . . . 12
  - 2.4.1 Simultaneous Localisation And Mapping . . . 12
  - 2.4.2 Terrain Based Navigation . . . 13
  - 2.4.3 Scan matching . . . 13

3 Experimental setup 14
- 3.1 Methods implementation . . . 14
- 3.2 Choice of relevant data . . . 15
- 3.3 Data representation . . . 16
- 3.4 Correlation method . . . 16
- 3.5 Considered areas . . . 17
- 3.6 Given mission . . . 18
- 3.7 Framework . . . 19
- 3.8 INS estimator . . . 19
- 3.9 Simulation . . . 21

4 Results 22
- 4.1 Trustworthiness ratio . . . 22
- 4.2 Precision improvement . . . 24
  - 4.2.1 Terrain Based Navigation . . . 25
  - 4.2.2 Scan Matching . . . 26
- 4.3 Discussion . . . 27

Conclusion 28

Introduction

With the increase in reliability and capability of robotic underwater platforms, the applications of these systems in military, archeology, oil and gas monitoring, and search and recovery roles have been increasing at a considerable rate. One of the common applications of unmanned underwater vehicles is the MCM, involving the detection, classification and localisation of underwater mines. In these cases, the mission performance is directly dependent on the accuracy of the navigation and pose estimation. MCM is phase based, in that it is defined around a set of stages including detection, classification, identification and neutralisation. In contrast to existing ship-based platforms, no single robotic platform is currently capable of completing all phases of MCM. To accomplish this, collaborating platforms are employed which are optimized for the specific MCM phase.

The success of this collaboration depends on accurate navigation. For example, during the detection phase, pose and localisation errors will be reflected in the positioning of detected objects. This localisation error could result in the need for higher effort in reacquiring the detected object by a new platform, requiring a search of the area again, or possibly never reacquiring the object. Therefore, accurate navigation and localisation, specifically in challenging seafloor environments where multiple mine-like objects may exist is key. In cases where the variance on the navigation error is unbounded, this may only be achievable with a considerable amount of overlap in the effort applied in each MCM phase, thereby increasing mission time and resource usage.

In contrast to aerial, surface and terrestrial robotic platforms, UUVs navigation is challenged by the environment in which the vehicle is operating. Above water systems have the option of leveraging Global Navigation Satellite System (GNSS) such as DGPS which provide stable navigation estimates and corrections. Due to high levels of attenuation, this capability is not available underwater. In this environment, navigation and positioning is mainly provided by simple dead reckoning [1], acoustic localisation such as Short Baseline (SBL) and Long Baseline (LBL) [2], and/or through the use of Inertial Navigation System (INS) [3]. Through-the-sensors methods are also being developed to require less infrastructure or reduce drifting. Those methods include, among others, Terrain Based Navigation (TBN) [4], [5], Simultaneous Localization and Mapping (SLAM) [6] or Scan Matching[7], [8].

In this report we will show the results of an analysis of performance of Terrain Based

Navigation (TBN) based algorithms with potentially sparse a priori data sets and of Scan Matching. This report is structured as follows: Chapter 2 will examine the current methods being used for underwater navigation. Chapter 3 will introduce both models used here, including a description of the data representation, and feature selection as well as the experimental setup. Chapter 4 will outline experimental results and conclusions to the analysis, as well as outlining future work.

Chapter 1

Context of the internship

This work was done during an internship in collaboration with Defence Research and Development Canada Atlantic Research Centre (DRDC) within the Mine Warfare group. DRDC is currently conducting a research programme into GNSS-denied navigation, specifically for Unmanned Underwater Vehicle (UUV) in MCM. One focus of this programme is the localization of a UUV performing a mission in a poorly known environment.

1.1 Research centre

Defence Research and Development Canada (DRDC) is an agency of Canada's Department of National Defence (DND). DRDC provides DND, the Canadian Armed Forces (CAF) and other government departments with the scientific and technological advantages they need to defend and protect Canada's interests. DRDC is comprised of 8 research center across Canada conducting research in cover a wide spectrum across all domains of concern to the CAF.

The DRDC - Atlantic Research Center (ARC) was first established in 1944. It was one of the originating organizations that came together in 1947 to form the Defense Research Board which later became DRDC. Located in Halifax, Nova Scotia, this research centre conducts research and development activities mainly related to the maritime defence such as :

— Antisubmarine warfare
— Mine and torpedo defence
— Shipboard command and control
— Naval platform technology
— Emerging materials
— Signature management
— Maritime information and knowledge management

— Virtual platforms and virtual combat systems

This internship is highly related to the mine defense, commonly referred to as Mine Countermeasures (MCM). The aim is to provide better navigation accuracy to deal with the issue presented in the next section.

1.2 Mine Countermeasures

The origin of naval mines is not completely known. Some have dated the first use back as far to the Ming dynasty [9] while others assert they only appeared during the American War of Independence. However, the application of mines has increased during the two last World Wars and more recently during the Gulf War. As a result, countermeasures have improved considerably in the last century. While it was mainly done through minesweeping using mine countermeasures vessels at first, it evolved into minehunting. Recently, UUV have been adopted for use in MCM. The mission of the UUV is to detect, classify, identify and neutralize naval mines. To do so, sonars are being used to try to detect the presence of suspicious items either on the seafloor or in the water column. Due to the specialization of the platform, one peculiar UUV is not able to fulfill all these goals. Collaboration between specialised robotic platforms is thus required. Consequently, accurate navigation is mandatory in order for each platform to be able to provide trustworthy data or to go to a precise location.

Eq. 1.1 aims to give a probabilistic point of view to the performance ofMCM, considering each phase of the process. Table 1.1 explains the terms used.

Table 1.1 – Equation 1.1 Terminology

P_{reacq}	: Probability to reacquire a given object
P_{dc}	: Probability to detect and to classify the naval mine
P_{ID}	: Probability to identify the naval mine
P_N	: Probability to successfully neutralize the naval mine

$$P = P_{dc} * P_{reacq} * P_{ID} * P_{reacq} * P_N \tag{1.1}$$

For collaborating AUVs, each phase and reacquisition probability must be considered in the overall performance. However, on a ship-based platform P_{reacq} is commonly considered as equal to 1 whereas when using UUV this assumption cannot be made. Furthermore, MCM planning requires an understanding of the navigation error to allow for track placement which minimize gaps in the data due to navigation error. This is not possible for AUVs where GNSS is not available, as this distribution can grow without bound. The improvement of GNSS-denied navigation accuracy is thus really important for MCM since it could provide a stable distribution of navigation error. As a result, the planning of MCM missions would be much simpler.

Chapter 2

Underwater navigation

The following chapter focuses on the techniques used in localization of UUVs. This is one of the key issues regarding underwater robotics. Indeed, some constraints are inherently linked with the subsea context :

— **No GNSS localization** - Due to high electromagnetic attenuation, GNSS services are unavailable once the UUV dive a few meters beneath the surface.

— **Computational cost** - When considering small vehicles, computational cost can impact not only range but also cost. The more energy-friendly the embedded systems are, the longer is the range. Low computational cost in navigation methods means that powerful processors are unnecessary, or allow processing capacity for other systems such as autonomy.

— **Noisy sensors** - The water is a challenging environment for sensing. While typically sonars are used, they suffer from environmental features.

— **Sparse maps** - As soon as your working area is not in an important harbour, maps can be sparse. This is particularly relevant concerning terrain-based navigation.

In this section, we will consider dead reckoning, Underwater Acoustic Positioning Systems (UAPS) and INS will be reviewed before focusing on Through The Sensors (TTS) methods.

2.1 Dead Reckoning

Typically applied to low-cost UUVs, dead reckoning approaches use a measurement of distance traveled and heading. These measurements are integrated based on a known start position, resulting in a position and pose estimate. Dead reckoning can be combined with velocity sensors such as a Doppler Velocity Log (DVL) and/or inertial sensors to increase accuracy. Although dead reckoning is a simple and low cost solution, the accumulation of errors in the navigation solution can continue without bound, and therefore is not applicable to underwater search where a high level of precision is required without some other method of error correction.

2.2 Underwater Acoustic Positioning Systems

The UAPS have the constraint of requiring the placement of additional infrastructure for localisation. This infrastructure is typically a set of buoys which need to be deployed before the mission. These buoys, equipped with either a fixed position or a GPS, can provide positioning updates through transmission and reception of acoustic pulses and time of flight measurements to determine a localisation solution. UAPS can be divided into three main methods :

— **Long Baseline (LBL)** - In the LBL case, transponders are placed on the seafloor far one from each other - usually on each corner on the working area. No device is subsequently on surface but it means that those transponders had to be accurately installed before the mission.

— **Short Baseline (SBL)** - Transponders are on a surface vehicle which have access to its global position over time. Since the transponders are much closer and that the ship is potentially moving, this solution is less accurate than with LBL and requires to have a vehicle on surface. However, no a priori installation is needed and if the working area dynamically evolves, the ship is able to follow the robot.

— **Ultra-Short Baseline (USBL)** - It basically is a lot the same than SBL except there is only one transponder. In order to compute the bearing, the robot must thus relies on the phase shift. It is even less accurate than SBL but is also less expensive and can be mounted on smaller ships.

Figure 2.1 – Acoustic positioning through baseline methods. Reproduced from [10]

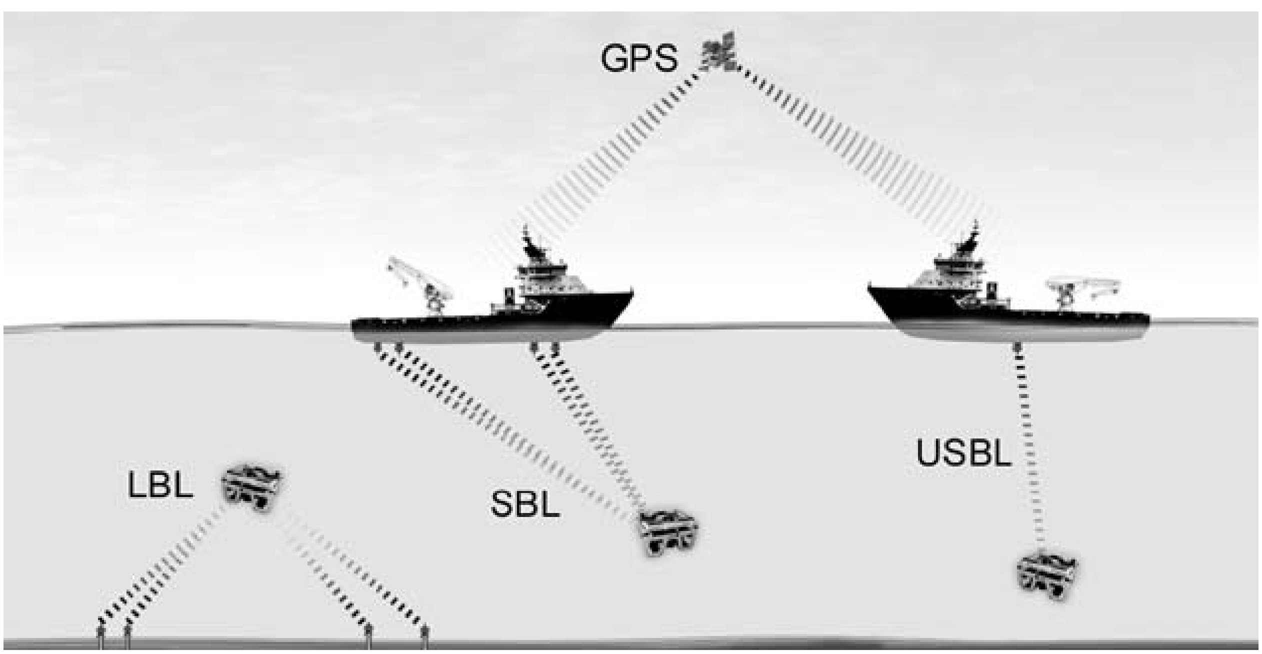


Fig 2.1 demonstrates the differences between these techniques. However, the infrastructure requirement can pose a challenge for MCM as it may not be feasible to deploy a

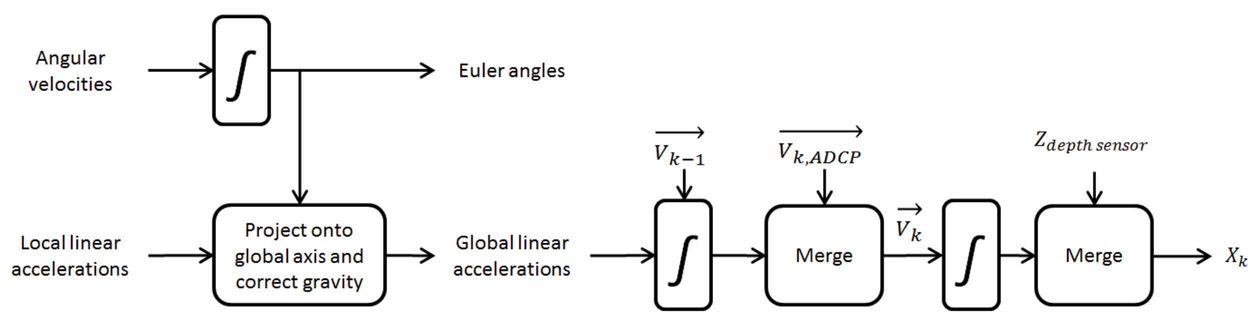
series of transponders or a ship to aid in underwater navigation due to hazards, traffic, ice coverage or a need to be covert. Moreover, UAPS is highly dependant on the environment such as the speed of sound and the bathymetry, therefore consideration must be given when placing infrastructure.

2.3 Inertial Navigation System

INS provides a method for underwater navigation which does not require additional infrastructure such as buoys. INS determines and maintains a navigation solution through the integration of measurements from heading sensors such as a ring laser gyro and accelerometers. These systems can further be aided through external sensors such as DGPS when available, and Acoustic Doppler Current Profiler (ADCP). Although INS based systems provide a considerable improvement in positioning accuracy over dead reckoning, these systems still contain sources of error on the accelerometers, heading measurement and aiding sensors. This error is composed of both drift and bias [3]. The bias can be measured and accommodated through calibration whereas the drift cannot. Although limited in comparison to unaided dead reckoning, the result of the accumulation of this error is a potentially unbounded growth of positioning uncertainty.

Fig 2.2 gives the main idea of the integration of sensors data in order to estimate the state vector. The fusion of measurements is commonly made thanks to Bayesian filters such as Kalman Filter (KF) - or its non-linear counterpart Extended Kalman Filter (EKF) - or Particle Filter.

Figure 2.2 – Exemple of the integration process commonly applied to INS navigation



Propagation of errors is an important part of the state estimation. [11] gives a good overview of noise models. It is composed of a constant bias, a white noise and a correlated random walk. Due to this noise model, one should note that the uncertainty growth is unbounded. As a result, this method alone is unsuitable for long missions.

2.4 Through-the-sensor methods

One recent technique for navigation and visual odometry which has gained widespread use is through-the-sensor (TTS) approaches. In these approaches, the vehicle will employ sensors to gather data which can be used to localise the vehicle and provide navigation updates. Those methods can be feature based or coherent methods which leverage Synthetic Aperture Sonar (SAS) [12], [13]. Two of the most common and related techniques are Terrain Based Navigation (TBN) [4] and Simultaneous Localization and Mapping (SLAM) [14]. While these techniques have been shown to be effective for navigation and pose prediction, they are dependent on a sufficient set of seafloor features to develop a positioning estimate. This set of unique features is one of the primary challenges for incoherent TTS methods which use image based correlation. Ideally, high fidelity maps would be provided to the UUV for image correlation, however in practice this data may be dated, sparse or of low fidelity. Determining the minimum feature set which is required to effectively navigate, as well as how the positioning capability will degrade with sparse maps is key to understanding the performance of the algorithm and assigning a confidence value to a positioning estimate.

2.4.1 Simultaneous Localisation And Mapping

Localizing landmarks to improve navigation is bit of a cause and effect dilemma. Nevertheless, it is at the root of numerous SLAM implementations. Indeed, SLAM aims at building a map of an unknown environment while concurrently using this same map to localize a vehicle. Using SLAM, a robot must create a map of an unknown area and use the generated map to localize itself. It usually relies on multiple observation of features or landmarks (assumed to be time invariant) to decrease position uncertainty of both the vehicle and the feature. It basically does an intersection of previously estimated uncertainty area with the currently computed one. Thus, it allows periodic compensation for the natural drift of an INS [15].

The main drawback of this technique is the increasing dimensionality of the state vector. Generally speaking, SLAM algorithms have a computational complexity in $O(n^2)$ [6] or in $O(n \log n)$ [16]. As a result, full SLAM implementation on tiny robots is challenging due to computational load, however lighter implementations begin to appear such as uFastSLAM [17].

Regarding the features, one part of designing a SLAM method will be to find a way to properly characterize those features. This characterization must be precise enough for the feature not to be mistaken with another, without being too constraining to recognize the feature later from a different point of view.

2.4.2 Terrain Based Navigation

Terrain Based Navigation (TBN) [4], [5], technique consists in using a priori knowledge of an environment. It thus requires both sufficient knowledge over the mission area and a sufficient variability of the data to allow for unique matches. Correlation between the currently visible characteristics and known features is then used to reduce uncertainty. To do so, the correlation usually provides the most coherent matches between the known characteristics and the sensed features. Thus, this method is not only able to bound the drift but can even improve the accuracy. The main difficulty of this method is to find a well known data set with enough variations and which could be measured in situ with enough precision. Those data must then be represented efficiently not to lose information keeping in mind computation power must be saved. In most of the cases, magnetic field maps [18] or depth maps [5] are chosen.

This method was being used before the widespread use of GNSS services. Indeed, it was first developed in the 60's to be employed in cruise missiles [19]. This version of TBN was called Terrain Contour Matching (TERCOM) since it was relying on correlating given contour maps with the sensed contour features. However, this needed the missile to fly a stable path. Although this method is still used nowadays, some others implementations have emerged such as the Sandia Inertial Terrain-Aided Navigation (SITAN) [20], Terrain Profile Matching (TERPROM) [21] or Digitized Scene-Mapping Area Correlator (DSMAC) [22].

2.4.3 Scan matching

Given the sparsity of underwater maps, a self-contained localization method which would not need any a priori data is interesting. SLAM fulfills this criteria but can be limiting due to high computational requirements. Scan matching could thus be an alternative. The idea is to use successive overlapping measures to compute the displacement between those measures. Hence it uses two successive measures, environment data such as the speed of sound can be considered constant. This independence from such parameters is really interesting since it removes some source of uncertainty. [7] and [8] give good illustrations of this method. However, one limitation of scan matching lies in its ability to decrease only the uncertainty accumulated since the last fix. Indeed, it is not able to give any hint of a global localization but only local fixes.

Chapter 3

Experimental setup

The following chapter will present the simulation setup and the TBN and Scan Matching implementations used in this work. The aim of the experiment is to simulate the output of two navigation methods, Terrain Based Navigation (TBN) and Scan Matching. To do so, the following section will use real bathymetry data from the Bedford Basin, INS trajectories will be simulated using a simple INS noise model inspired from [11]. The actual planned tracks degraded through the noise model described in [11].

3.1 Methods implementation

Although their application is not the same, Scan Matching and TBN are similar in the method in which they can be implemented. On both cases, a feature correlation method has to be selected. In our case, we leverage computer vision algorithms for doing so. Considering [23], Scale-Invariant Feature Transform (SIFT) [24] and Speeded Up Robust Features (SURF) [25] are commonly used algorithms for TBN. Indeed, seven algorithms are compared in [23] by asking them to find matches in different tiles. SIFT and SURF are the most balanced algorithms as they successfully provide good matches in most cases. In our application, since SURF is faster than SIFT, it was used as the matching algorithm. Methods not relying on vision algorithms, such as Iterative Closest Point (ICP), can be found [7], [8].

As we employ vision algorithms, sensed data will have to be represented in an efficient way. Moreover, as the results will not be always significant due to potential high uncertainty, a metric to weight the output confidence is crucial.

Finally, the difference between TBN and Scan Matching is that the former performs the correlation between a known map and current measures while the latter correlates between two successive overlapping measures.

Fig 3.1 gives an example of TBN correlation while Fig 3.2 gives an example of Scan matching correlation.

Figure 3.1 – Correlation of features between the scanned image and the a priori map as is used in TBN showing estimated position in the map

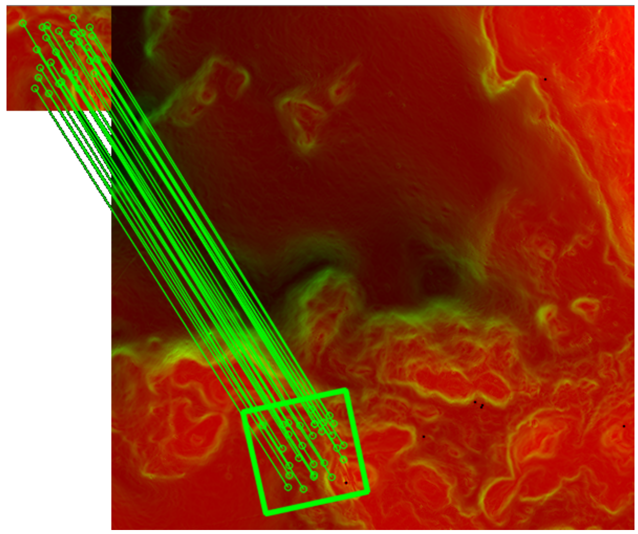
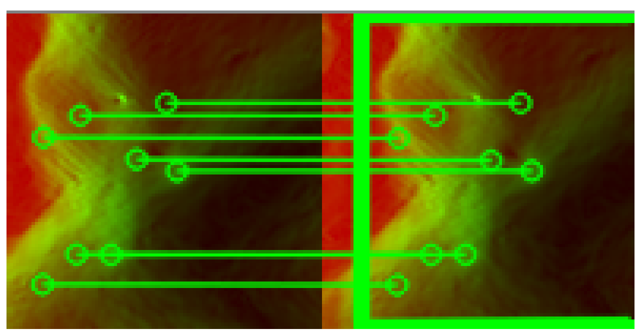


Figure 3.2 – Correlation between two sonar measures as is used in Scan Matching showing estimated displacement between the two measures



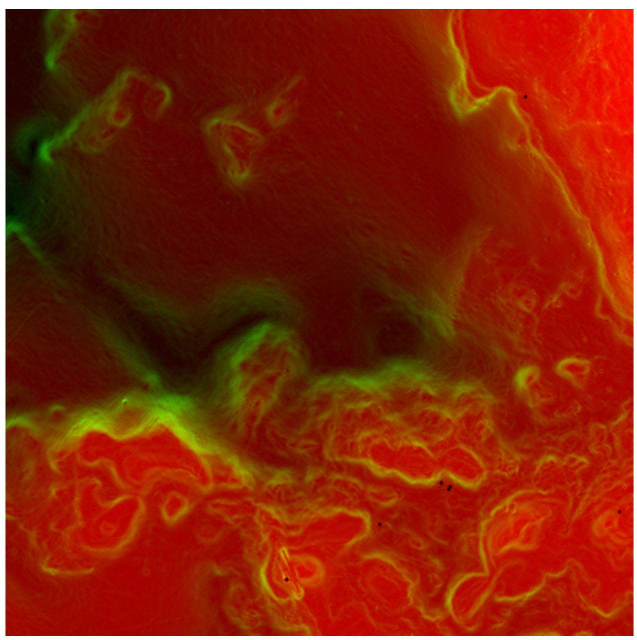
3.2 Choice of relevant data

First of all, we must choose which features will be considered relevant. Ideally, chosen feature must be detailed to allow matches and varying enough to allow unique or locally unique correlations. As high fidelity bathymetric maps will be used in the incoming simulations, features will be extracted from depth related information. The depth is the most obvious feature given by bathymetric sonars. However, it is not necessarily the most reliable. Indeed, bathymetric sonars can give depth relative to the robot depth. To determine global depth, the robot depth must be precisely known which could theoretically be done thanks to a depth sensor and knowing the tide level. Through this sum of uncertainty, depth is not completely trustworthy, as same measurement noise will be observed. A depth invariant data would thus be really useful. Thanks to the relative depth map, we can compute an absolute gradient map. While a given depth would nearly always be present in different place, a given couple of depth and gradient is much more unique. Moreover, two data can be extracted from gradient, its norm and its direction.

3.3 Data representation

By splitting the gradient map into a norm map and a direction map, we end up with three different data. Given those, an image can easily be made. The choice of the color model (e.g. Red Green Blue (RGB) and Hue Saturation Value (HSV)) is at the discretion of the reader. Initially, we used HSV since the H layer is represented through an angle which is related to the gradient direction. However the implementation of the data representation uses the OpenCV library which relies on a 8 bit encoding for its image. As a result, the hue values were bounded into $[0, 180]$. As a result, the representation is less accurate as more values will be concatenated in the same resulting hue value, therefore losing fidelity in the feature. Thus the RGB color model was chosen to encode the features and one feature value was attributed to each layer. The example of such an image is 3.3.

Figure 3.3 – Resultant image of a given area



3.4 Correlation method

Given two images, feature matching is then done thanks to nearest neighbors algorithms. To do so, we used the Fast Library for Approximate Nearest Neighbors (FLANN) and k-d trees to reduce the computational time [26]. This matching provides the two best solutions for each SURF descriptors. Thanks to those two matches, correct ones are kept based on the Lowe's ratio [24] which provides a threshold for when the probability of a false match became greater than the probability of a true match. Even if this ratio was given for SIFT, SURF is drawn from SIFT so this limit is still relevant. One could also suppose there is a correlation between the number of good matches and the final precision. Consequently, finding this underlying ratio can be interesting to characterize the output confidence. Based on this described method, the algorithm detailed in Algorithm 1 will be used.

Algorithm 1: Algorithm used for correlation and estimation of displacement in the following report

---

Data:
Current Measure : M_k
SURF descriptors of previous measure (SM) or known map (TBN) :
$SURF\_Descriptors_{knowledge}$

Result:
Rigid transformation rotation : R
Rigid transformation translation : T
Confidence in the outputs : Γ

$I_{measure}$ = DataRepresentation(M_k)
$SURF\_Descriptors_{measure}$ = SURF($I_{measure}$)
$Matches$ = knnMatcher($SURF\_Descriptors_{knowledge}$, $SURF\_Descriptors_{measure}$)

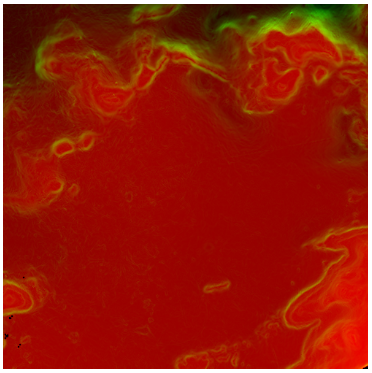
$GoodMatches$ = []
foreach $BestMatch_1$, $BestMatch_2$ *in* $Matches$ **do**
    if $BestMatch_1$ *and* $BestMatch_2$ *satisfy Lowe's ratio* **then**
        Add $BestMatch_1$ to $GoodMatches$

Γ = TrustworthinessRatio($GoodMatches$)
R, T = EstimateRigidTransform($GoodMatches$)

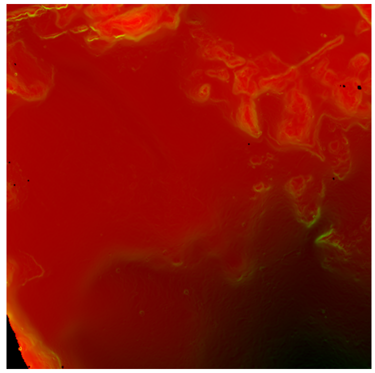
3.5 Considered areas

All the areas considered are extracted from a bathymetric map of the Bedford Basin in Halifax, Nova Scotia. This map was provided by the Canadian Hydrographic Service and is 2 meters precise. Three areas were extracted from this map for their potential features concentration which means their gradient and depth variability. Using the encoding technique representation described in Section 3.3, they are represented in Fig. 3.4. To be able to observe the influence of the precision of a priori knowledge, less precise maps were created by decimating the map and interpolating across samples using an implementation of bi-cubic interpolation.

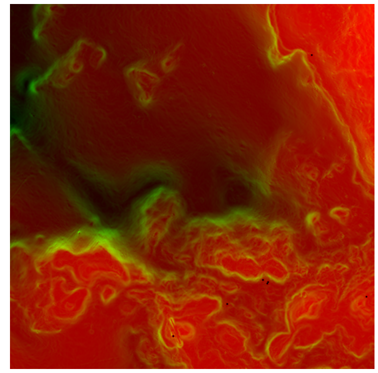
Figure 3.4 – Areas used in the simulations



(a) Area 1 - Medium concentration of features



(b) Area 2 - Low concentration of features

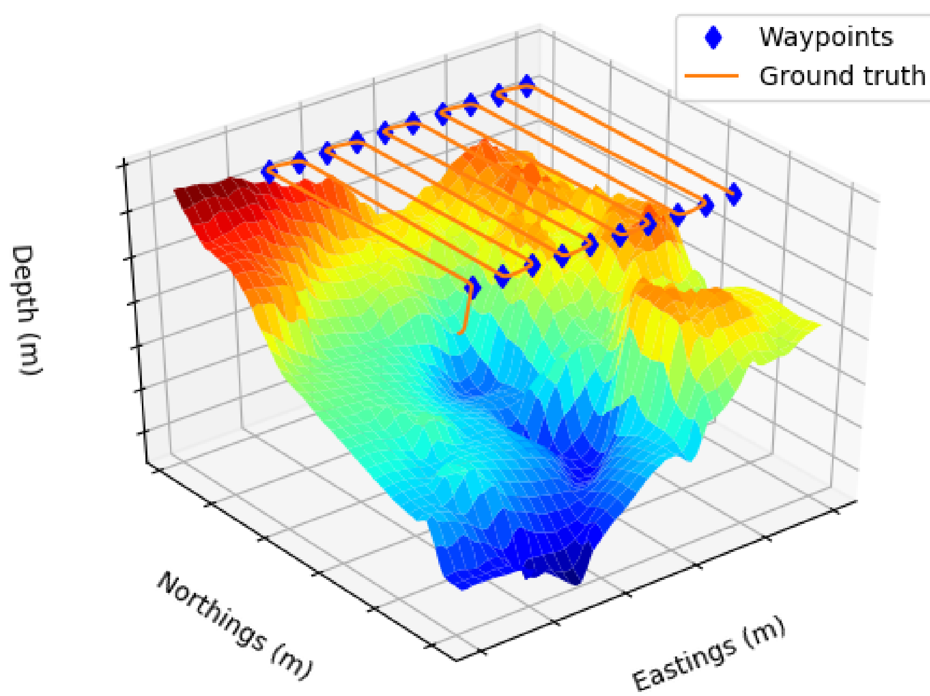


(c) Area 3 - High concentration of features

3.6 Given mission

The missions given to the robot were lawn mower trajectories. This kind of trajectory is commonly used when searching an area for mines. Moreover, it often provides overlapping measures when the lines are close enough one to another. Fig. 3.5 gives an example of such a simulated trajectory.

Figure 3.5 – Simulated mission showing the lawn mower trajectory of the robot over one the selected area



3.7 Framework

In order to have a coherent simulation easily reconfigurable, a custom framework has been developed in Python. The purpose of this framework was to allow an easy comparison between the ground truth trajectory of a mission and estimated trajectories computed by various estimators. Since series of simulations were required in order to have relevant statistics, a special attention was given to compute once for all constant data. As we required vision algorithms, OpenCV was chosen which binds directly with Python.

Some improvements are still to be made to this framework. A physical engine would for instance be of great help to simulate a more realistic behavior for the sensors.

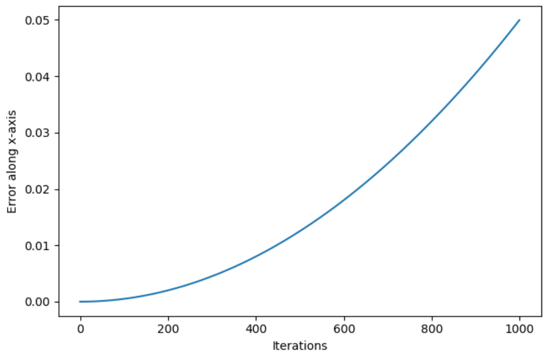
3.8 INS estimator

The navigation error estimator which was implemented is a INS one. It uses generated Inertial Measurement Unit (IMU) measures and Kalman filters to provide coherent estimation. The IMU measures are degraded according to the models given in [11]. Similarly to their simulator, only constant bias, white noise and correlated random walk was considered in this simulator. As a result there is an unbounded drift of the uncertainty. However, since the constant bias can be dealt with through calibration, no noise of this kind was used.

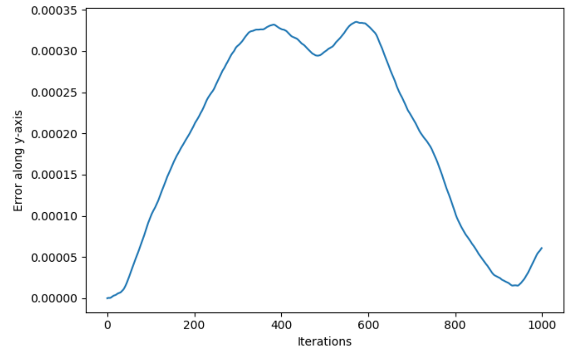
Fig 3.7 and Fig 3.6 aim to help understand the behavior of this simulator by presenting noisy measures and the resulting integration on each axis. For both figures, the IMU does not move during the simulation. Thus the output highlights the induced drift. For this simulation, a constant bias was applied on the x axis, a white noise on the y axis and a random walk on the z axis.

Figure 3.6 – Integration of measures along each axis showing the drift induced by each kind of noise

(a) Constant bias influence on x axis



(b) White noise influence on y axis



(c) Correlated random walk influence on z axis

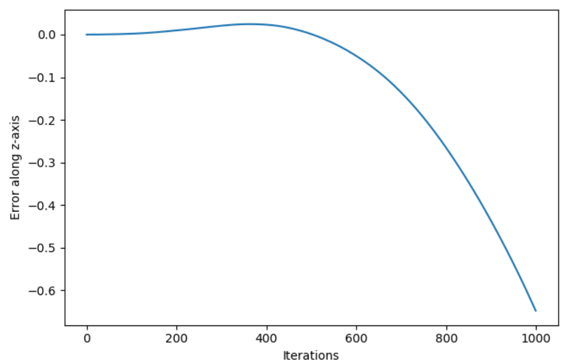
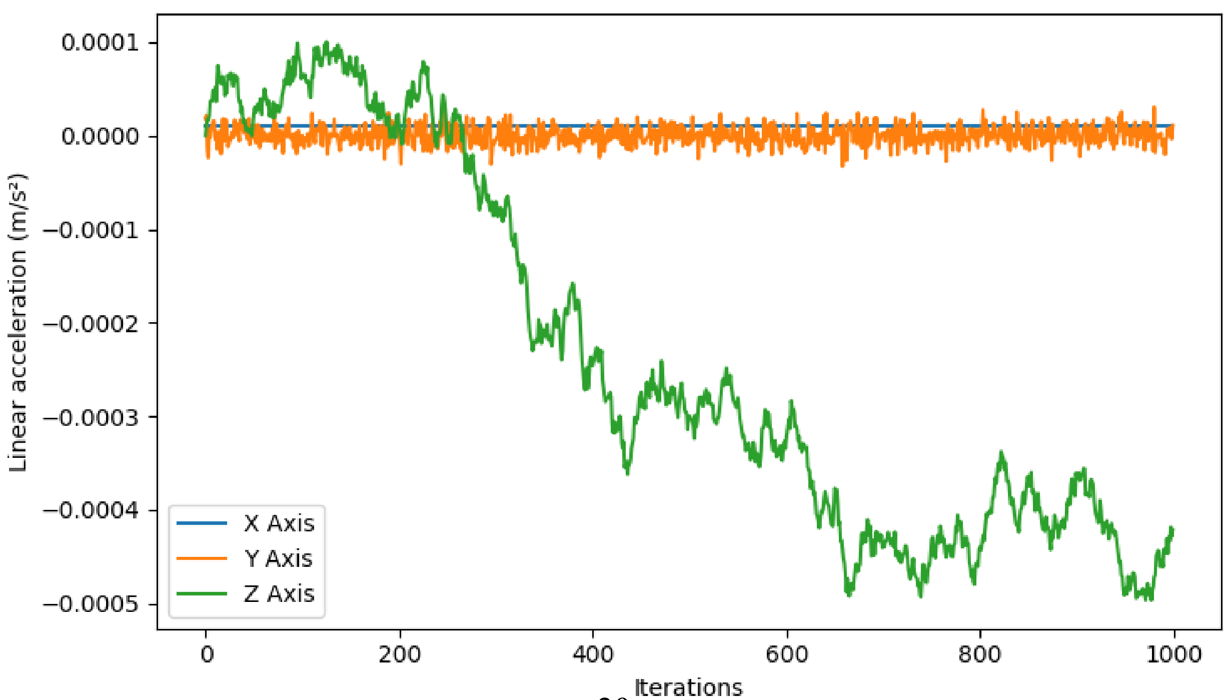


Figure 3.7 – Linear accelerations output showing the behavior of noises



Finally, when used to estimate a trajectory, the output is coherent with a natural INS behavior as shown in Fig 3.8.

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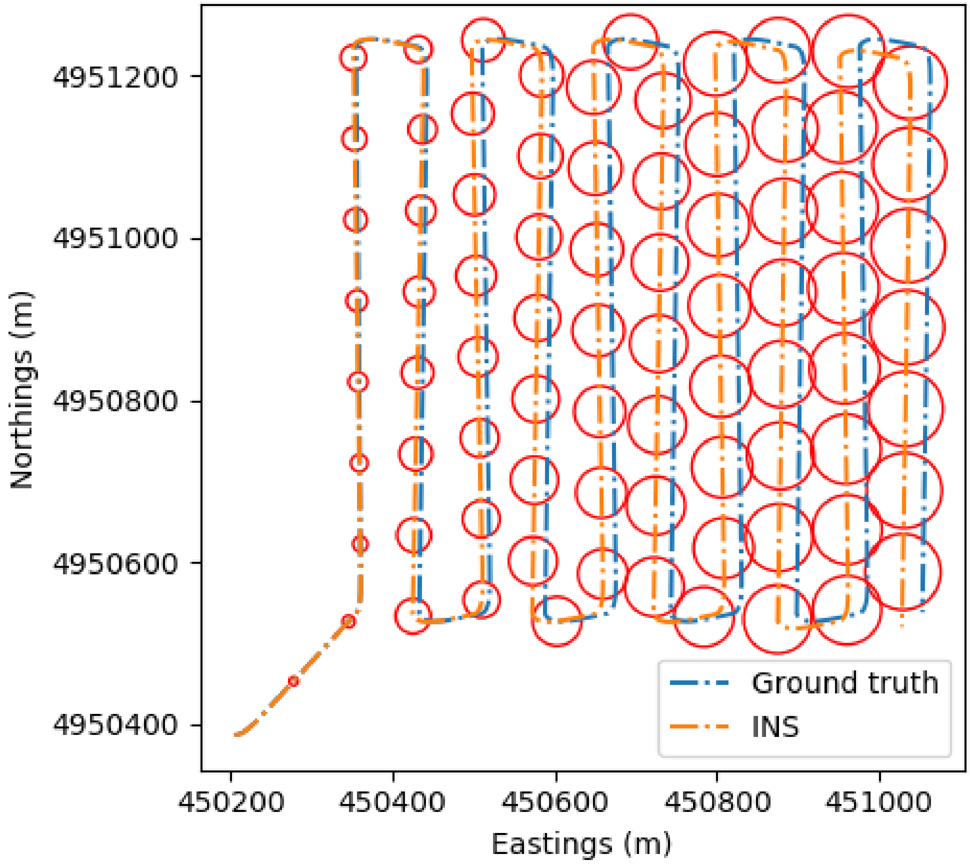
Figure 3.8 – INS trajectory example with linear accelerations noises showing the drift and uncertainty induced by the noise model



3.9 Simulation

Two aspects were considered during those simulations. First, the evolution of the precision related to the number of good matches and the Lowe's ratio of those matches is dealt with. Then in a second serie of simulations, the improvement obtained thanks to TBN and Scan Matching is highlighted. For this second part, the results presented in the next section were obtained as followed. For each couple of area and precision of the grid, 1000 iterations were completed. For each iteration, the noise interfering with the INS was randomly generated following the model given in [11]. Scan Matching and TBN estimators were then asked to try to improve the navigation. Consequently, each data in the following curves correspond to the mean of 1000 results.

Chapter 4

Results

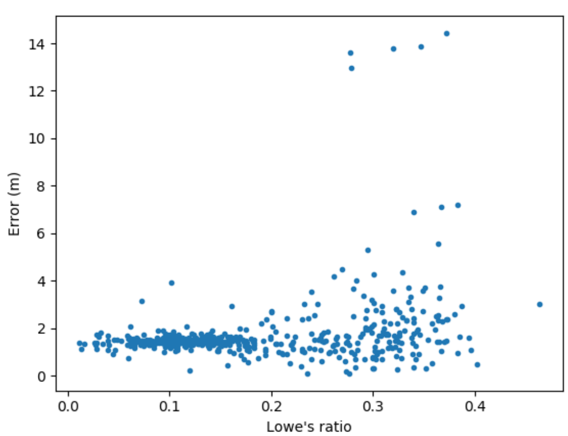
4.1 Trustworthiness ratio

Two data are at our disposal in order to try to find a kind of trustworthiness ratio regarding the output of the algorithm **??**. Those data are the number of good matches and the Lowe's ratio [24] of each one of those good matches. A lot of correlation such as the one presented in Fig. 3.1 were done knowing the exact position of the small picture in the second one. Thus, by comparing the position given by the algorithm and the true one the accuracy was computable.

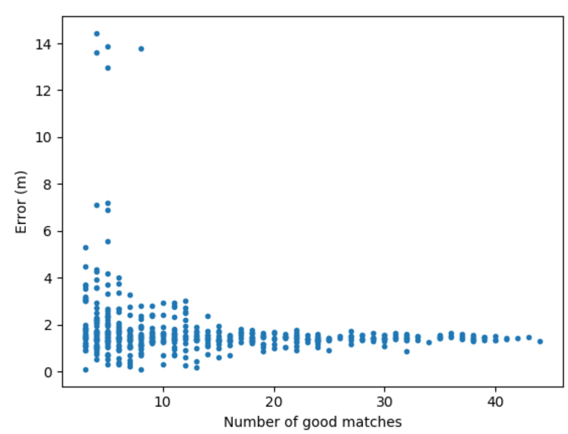
Fig. 4.1a highlights the distribution of the accuracy depending on the mean square of the Lowe's ratio while Fig. 4.1b shows the same repartition of accuracy but in regard of the number of good matches.

Figure 4.1 – Correlation between accuracy and Lowe's ratio or number of good matches

(a) Lowe's ratio



(b) Number of good matches



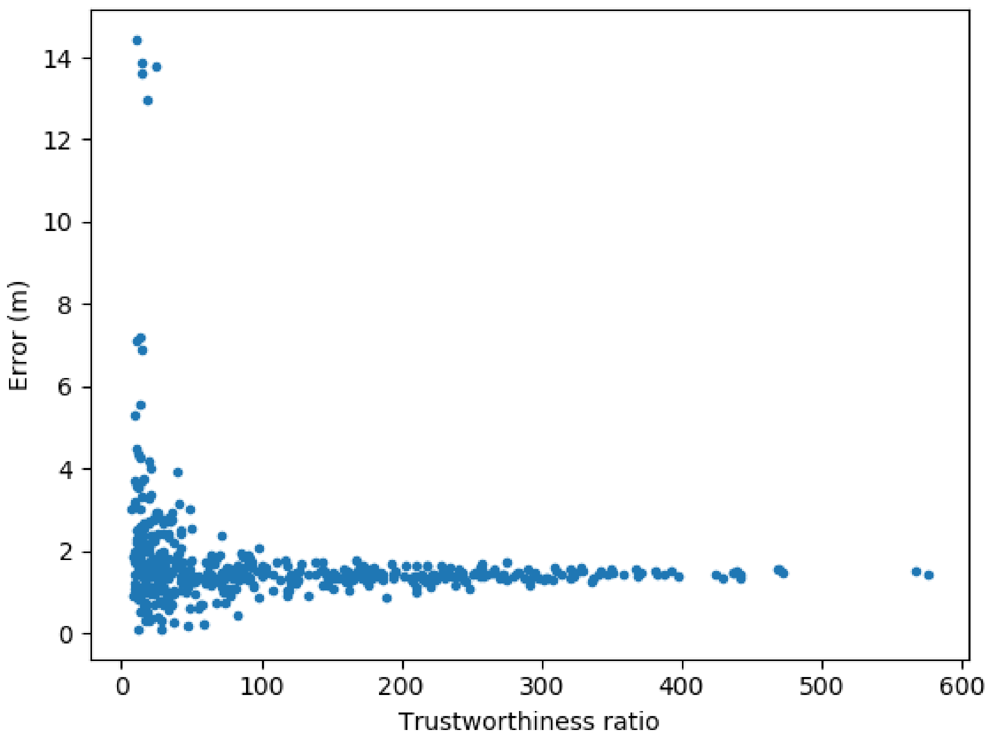
Considering those results, it seems that the trustworthiness ratio can be built regarding the number of good matches and the inverse of the Lowe's ratio. Moreover, to discriminate more clearly the results, we will not take the mean of Lowe's ratio but the mean square.

Taking the mean square rather than the mean allows to weight more the Lowe's ratio, as a result fewer matches of high probability to be good are preferred to many lower probability matches. The chosen ratio is thus:

$$\text{Ratio} = \frac{\text{Number of good matches}}{\text{Mean square of Lowe's ratios of the good matches}} \tag{4.1}$$

Thanks to Eq. 4.1, we obtain the results shown in Fig. 4.2.

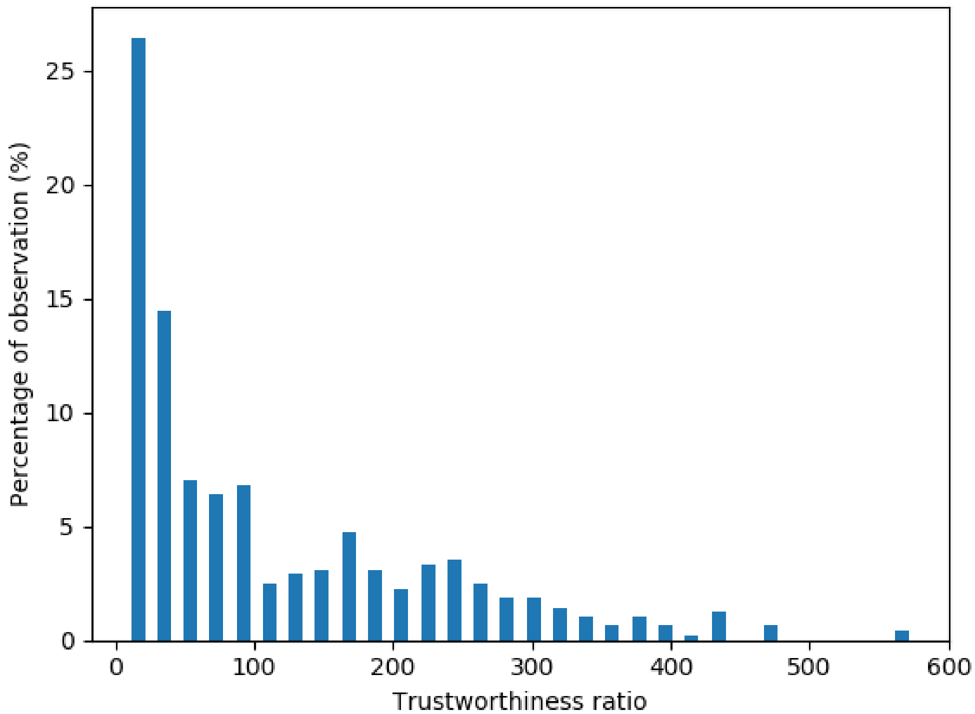
Figure 4.2 – Trustworthiness ratio showing the evolution of error depending on the trustworthiness ratio



One can observe that the ratio defined in Eq. 4.1 seems to provide a good output discrimination. Although the mean error appears to be constant regardless of the ratio, the standard deviation is clearly improving with it. As a result, a good precision allows one to define a confidence for the outputs. It is precisely this confidence which is important to properly merge observations in a Bayesian filter. It should be noted in Fig. 4.2 that an ambiguity is still present when the score is low, some improvements could probably be made.

However, when looking at the distribution of those observations as displayed in Fig. 4.3, it appears that a low score on this ratio is common. One should thus really consider changing the confidence given to output rather than simply rejecting some observations. Even when the score is low, most observations have a accuracy error below 5 meters which is far from being irrelevant considering the map surface is 1 kilometer square.

Figure 4.3 – Observations distribution regarding trustworthiness ratio showing that most observations obtain a low score and thus are in the ambiguity zone



4.2 Precision improvement

All the following results will be presented according to three data. First, the improvement percentage compared to the INS navigation. 0% will correspond to no improvement at all, 100% is a perfect navigation and a negative percentage corresponds to worsening the navigation. After that, the time taken to compute one observation on average is considered. These times are highly dependent on the computer however the general evolution is important. And finally a weighting of the precision gain by the time. Calling this variable G and given that MSE_x and t_x corresponds respectively to the mean square error and the time linked to a certain method x, the computation is done as follows:

$$G = \frac{MSE_{INS} - MSE_{method}}{t_{method}} \tag{4.2}$$

Thus, we obtain a value representing the precision gained compared to the INS alone by time spent on computation.

For the improvement percentage and the time taken, errors bars are displayed and represent the standard deviation (1σ) of the results. It roughly means that two thirds of the occurrences are within this interval.

4.2.1 Terrain Based Navigation

During the navigation simulations, the precision of the known map was degraded iteratively from a 2 meters precision to a 10 meters precision. The aim was to find the evolution of the navigation accuracy and also the time required for processing the solution. Indeed, as the precision of the map decrease the SURF algorithm will be faster.

In the figure 4.4a, we observe a substantial growth of the uncertainty as the precision of the grid decreases. Moreover, this figure highlights that past a certain degradation of the map, the standard deviation shows that the method could in fact degrades the navigation. However, we can also see that the computational time is increasing with the precision, caused by the increasing dimension of the a priori map.

The importance of a compromise clearly appears when using the previously explained ratio. In the figure 4.5, one can observe that the optimal choice is more than twice more effective than by simply taking the most accurate case.

(a) Accuracy improvement (b) Time taken

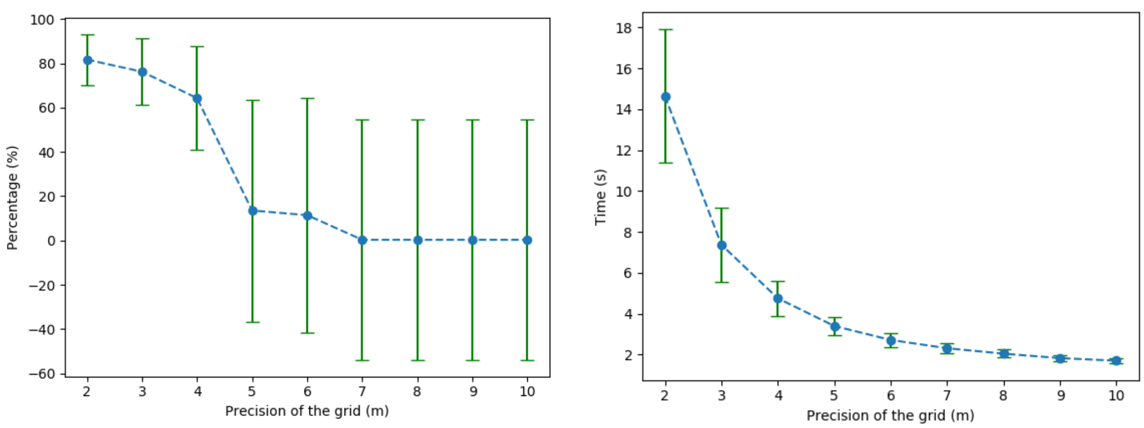
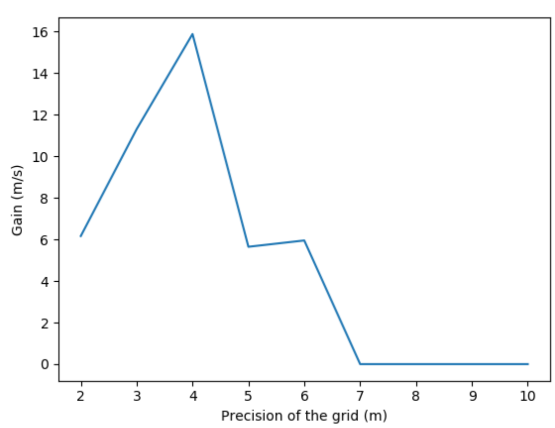


Figure 4.4 – TBN results

Figure 4.5 – Weighting of accuracy improvement by the time spent on computation showing potential most efficient cases



4.2.2 Scan Matching

In this case, the overlapping area between two successive measures was becoming smaller between each simulation. The percentage on the x-axis represents the percentage of overlapping between two measures. Obviously, an useful overlap means a more precise navigation. But again there is a limit where the method can in fact degrade the navigation, as by decreasing the overlap the uncertainty of the output will grow. Moreover, one can observe that the time required for each iteration is much lower than compared with the TBN method. However, the average gain is lower than with the previous method since it is unable to reduce uncertainty more than the error accumulation since the last scan matching observation. Still, there is a notable improvement compared with the INS alone.

(a) Accuracy improvement

(b) Time taken

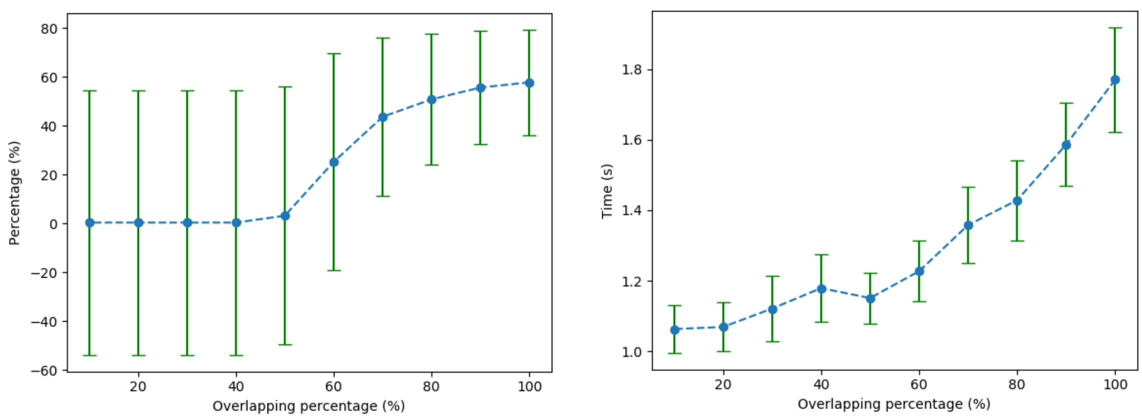
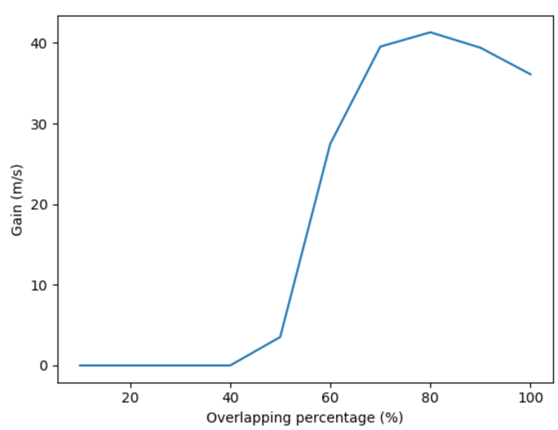


Figure 4.6 – Scan Matching results

Figure 4.7 – Weighting of accuracy improvement by the time spent on computation showing potential most efficient cases



4.3 Discussion

Both methods are highly dependent on the concentration of potential features. Those features can be depth-related like the one used in this report or other features as long as locally unique correlations are possible. Additionally, they demonstrate the same behavior regarding degradation of the data. The trend on accuracy is similar with a sudden drop on accuracy which lead to an inaccurate output since the standard deviation of the error becomes too high.

Considering the dependence on the environment properties, TBN is far more dependent than Scan Matching. Indeed for better results TBN must know the speed of sound as well as the tide levels. Without those data, the estimation of the depth will be degraded. Scan Matching does not require this knowledge since correlation are made between two successive measures. As a result, both measures will have undergone the same degradation of depth estimation.

From a computational power requirements point of view, both methods complexities is $O(n^2)$ due to the SURF algorithm. However, one should take into account that Scan Matching correlates two subsequent pings or images which are in theory smaller than an a priori map. As a result, Scan Matching is faster than TBN.

To conclude, those two methods should be considered as complementary. Indeed, their main purpose is not the same. Whereas scan matching provides local fixes to limit the uncertainty growth, TBN gives global fixes to decrease it. Thus, even the values obtained through the equation 4.2 are not comparable. Indeed, one could think that Scan Matching is far more efficient than TBN since the maximum value of the ratio is around 40 m/s for the former and around 16 m/s for the latter. But if we look to the average improvement percentage of the navigation, TBN is more effective. Table 4.1 sums up those results.

Table 4.1 – Sum up of the differences between TBN and Scan Matching

<table>
<tr><th></th><th>TBN</th><th>Scan Matching</th></tr>
<tr><td>Fixes</td><td>Global</td><td>Local</td></tr>
<tr><td>Feature requirements</td><td colspan="2">Locally unique correlation</td></tr>
<tr><td>Environment</td><td>Dependent</td><td>Independent</td></tr>
<tr><td rowspan="2">Computational time</td><td colspan="2">Both $O(n^2)$</td></tr>
<tr><td>Big n</td><td>Small n</td></tr>
</table>

Conclusion

The goal of this internship was to assess the ability of Terrain Based Navigation (TBN) and Scan Matching to improve navigation for Mine Countermeasures (MCM) missions. Those methods were implemented using the Speeded Up Robust Features (SURF) algorithm and the kD Nearest Neighbors matching method. Having different aims, Terrain Based Navigation (TBN) and Scan Matching can really be used as complementary methods. Whereas the former provides global fixes and is thus able to decreases uncertainty since the beginning of the run, the latter can slow down the growth of this uncertainty. TBN is highly dependent on the environment characteristics since it must have a good knowledge of the feature map, the speed of sound and the tide levels. On the contrary, Scan Matching have the advantage not to require any a priori knowledge nor any environment parameters. Based on the results presented in this report, both methods appears to provide good improvements as long as available data are precise enough.

The trustworthiness ratio can most certainly be improved to better discriminate good estimates from bad ones. Indeed, if this discrimination is improved both methods will be more precise. As a result, it would be possible to decrease the uncertainty of the observations which would result in smaller standard deviation of the precision. Consequently, it would not only improve the precision but also allow TBN methods to use more degraded data.

Considering the TBN implementation, one idea could be to correlate the sensed data not to the entire map but to a part of a map where the probability for the robot to be present is highest. It would not only decrease the time of computation but also potentially decrease the number of wrong matches.

Finally, regarding the Scan Matching, testing its viability with a forward looking sonar would be interesting. Indeed, a forward looking sonar would provide huge overlapping between two successive measures.

Generally speaking, an implementation on a real vehicle would be really interesting in order to determine the real behavior of those methods. Moreover, it would also help calibrate the confidence given to each correlation. In addition, more studies in feature poor environments would be interesting in order to see if in this type of environment methods are useless. New methods or different feature could be used to improve navigation in those environments.

List of Figures

2.1 Acoustic positioning through baseline methods. Reproduced from [10] . . 10
2.2 Exemple of the integration process commonly applied to INS navigation . 11

3.1 Correlation of features between the scanned image and the a priori map as is used in TBN showing estimated position in the map 15
3.2 Correlation between two sonar measures as is used in Scan Matching showing estimated displacement between the two measures 15
3.3 Resultant image of a given area 16
3.4 Areas used in the simulations 18
3.5 Simulated mission showing the lawn mower trajectory of the robot over one the selected area 18
3.6 Integration of measures along each axis showing the drift induced by each kind of noise 20
3.7 Linear accelerations output showing the behavior of noises 20
3.8 INS trajectory example with linear accelerations noises showing the drift and uncertainty induced by the noise model 21

4.1 Correlation between accuracy and Lowe's ratio or number of good matches 22
4.2 Trustworthiness ratio showing the evolution of error depending on the trustworthiness ratio 23
4.3 Observations distribution regarding trustworthiness ratio showing that most observations obtain a low score and thus are in the ambiguity zone 24
4.4 TBN results 25
4.5 Weighting of accuracy improvement by the time spent on computation showing potential most efficient cases 25
4.6 Scan Matching results 26
4.7 Weighting of accuracy improvement by the time spent on computation showing potential most efficient cases 26

Glossary

ADCP Acoustic Doppler Current Profiler. 11

CAF Canadian Armed Forces. 7

DND Department of National Defence. 7
DRDC Defence Research and Development Canada. 7
DSMAC Digitized Scene-Mapping Area Correlator. 13

EKF Extended Kalman Filter. 11

FLANN Fast Library for Approximate Nearest Neighbors. 16

GNSS Global Navigation Satellite System. 5, 9, 13

HSV Hue Saturation Value. 16

ICP Iterative Closest Point. 14
IMU Inertial Measurement Unit. 19
INS Inertial Navigation System. 5, 9, 11, 12, 14, 19, 21, 24, 26, 29

KF Kalman Filter. 11

LBL Long Baseline. 5, 10

MCM Mine Countermeasures. 2, 5, 7, 8, 10, 28

RGB Red Green Blue. 16

SAS Synthetic Aperture Sonar. 12
SBL Short Baseline. 5, 10
SIFT Scale-Invariant Feature Transform. 14, 17
SITAN Sandia Inertial Terrain-Aided Navigation. 13
SLAM Simultaneous Localization and Mapping. 5, 12, 13
SURF Speeded Up Robust Features. 14, 17, 25, 27, 28

TBN Terrain Based Navigation. 2, 3, 5, 12–15, 21, 25–29

TERCOM Terrain Contour Matching. 13

TERPROM Terrain Profile Matching. 13

TTS Through The Sensors. 9

UAPS Underwater Acoustic Positioning Systems. 9–11

USBL Ultra-Short Baseline. 10

UUV Unmanned Underwater Vehicle. 7–9

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