Preface

This review presents a short summary of intelligent autonomous underwater vehicles (AUVs) and the use of data-driven control strategies. The text focuses on new techniques for data collection with AUVs, and the application of machine intelligence and spatial statistics. The reader is assumed to be familiar with basic concepts in marine robotics, including some general knowledge of AI, ML, and Spatial Statistics.

The current report is an updated version of the original dated August 2016.

The work is supported by a PhD scholarship from The Research Council of Norway, under the AMOS Center of Excellence, project number # 223254.

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1 Introduction

The backdrop for this review is rooted in ocean observation and monitoring, using machine intelligence to extend autonomous underwater vehicle (AUV) data collection capabilities. AUVs have provided scientists with a powerful tool for oceanographic research, and have changed the way ocean science is conducted, but the potential for further innovation is still great. The drive for this is twofold; sustainability and management of natural resources is regularly cited as the biggest problem of our generation. The ocean plays the central role as both a resource and early indicator for climate change, and the AUV is the tool which is best suited to provide the facts necessary for decision makers. Secondly, data collection at sea is still a challenging and an expensive enterprise; most AUV control agent systems today rely on a pre-programmed plan [27], consisting of sequential behaviors scripted with mission planning tools. This notion is not only restricted to the field of marine robotics, but information gathering platforms in general. Creative and novel solutions are therefore imperative, and constitute an excellent field for research.

![REMUS 100 type AUV traveling underwater.](image)

A defining weakness for non-adaptive information collection is the lack of flexibility and situational awareness; in addition, all knowledge is static and implemented a priori. Generally, knowledge is not readily available, incomplete, and include significant uncertainty. Driven by these factors, the demand for adaptive and more advanced autonomy concepts is contemplated across a wide range of autonomous research [9, 33, 19, 16, 46, 26]. The notion of dealing with; autonomy, adaptation/re-planning, and computational search between different action outcomes, are ideas central to the fields of artificial intelligence (AI) and machine learning (ML). For AUV, having these tools onboard is a prerequisite for adaptation and reasoning about uncertainties that arise in-situ. Opening up the possibilities of opportunistic concepts, allowing the AUV to divert form the mission if favorable circumstances would materialize. In sum, these factors provide means to increase the prospect of retrieving pursued information, which is why the data-driven/adaptive approach is becoming the new modus operandi for AUV control agents.
Clarification of some of the expressions used in this review. Note that the some of the terms have contextual connotations.

1. **Autonomy**: The word autonomy is extensively used and is presented as the definition given in Russel & Norvig (1995, p.34):

   "A system is autonomous to the extent that its behavior is determined by its own experience."

   Also, the following meanings are associated with autonomy: self-governing, self contained, and independent. However, the use of the word in this review is in a stronger sense defined towards self-control compared to just "Independent from human control".

2. **Autonomous Agent**: As given in Russel & Norvig (1995, p.31):

   "An agent is anything that can be viewed as perceiving its environment through sensors and acting upon that environment through effectors."

   Agent will be used as a description of the actual agent program that will be responsible for execution of the AUV behavior. The internal structure and properties of this program will be referenced to as the architecture. It will be implicit that the agent program is autonomous and is acting based on an intelligent utility.

3. **Machine Intelligence**: An expression to consolidate systems using artificial intelligence and machine learning.

4. **Deliberate and Reactive**: Terms used to describe properties of the different agent designs and/or architectures. The Reactive description encapsulates agent characteristics that are designed to act as a reflex, without any time consuming contemplation (Sense $\rightarrow$ Act). On the other hand, Deliberative features will involve processes similar to thinking, using internal states and behavioral mappings to decide what to do next; without strict time constraints (Sense $\rightarrow$ Plan $\rightarrow$ Act).

5. **Planning**: The term is used in many areas and is in this context used to cover the agent program process of finding a sequence of actions that transform the initial state to a goal state, subjected to a set of constraints. Note that planning is essentially different from a forecast or prediction; it is a statement of intention. Automated planning is an area usually connected with the field of AI. A planning algorithm is sound if invoked on a problem $P$ returns a plan which is a solution for $P$. A planning algorithm is complete if invoked on a solvable problem $P$ is guaranteed to return a solution.

6. **Data-Driven/Information Driven Sampling**: This phrase will be used to address algorithms that explicitly use previously collected data to infer the subsequent data collection strategy. This ties back to planning, in particular to sensor-based planning, which can be described as a plan constructed on the basis of past and current data.
2 Related work

The growing interest for developing AUVs to operate with a higher concept of autonomy spans several sub-fields including guidance and control theory, path planning, AI and ML, and spatial statistics to mention a few. A general introduction to the field of marine robotics with examples from field surveys can be found in [43]. Also, a summary to the past, current and future state of AUVs can be found in [48]. The pros, cons, and potential future of AUVs as research vessels is discussed in [16]. Literature concerning more traditional data collection with AUV for both benthic, and upper water column observation, is plentiful, see e.g. [17, 39, 15, 28] for examples. The current state of the art in path planning methodologies for long duration missions with AUVs is provided in [52], together with a categorical overview over the different classes of AUV, reproduced in Appendix A. In [14] a discussion on challenges for AUV autonomy, from the standpoint of the Norwegian Defense Research Establishment (FFI) is given, following the development of the pioneering AUV craft Hugin 3000. A more detailed and broad review of marine autonomy is given in [41], covering major topics on autonomy and cooperative applications. The publication also presents fully-fledged autonomous agent architectures used in scientific AUV applications; namely the T-REX (Teleo-Reactive Executive) developed at Monterey Bay Research Institute (MBARI) and MOOSE-IvP (Mission Oriented Operating Suite) from MIT. Being in regular operational use, the T-REX architecture have been exploring adaptive data-collection using multiple control loops together with a "divide-and-conquer" problem-solving strategy. A thorough overview is also given in [27] and [34], with the latter including examples from field implementation. Rolling out several advanced concepts, a step back to a more simple and intuitive approach to AUV autonomy is given in [5]. Here, demonstration and comparison of different Behavior-based AUV control approaches is given, using a simulated underwater environment. Further material from the same research group concerning recent trends in control architectures for AUVs can be found in [36, 37].

Advances in AUV autonomy have in recent years developed to include information/sample driven approaches, as coupling with AI and ML emerge as a toolset strategy to handle uncertain and dynamic coverage problems. Often associated with the field of path planning, the early adaptations started in the early 90s with using potential fields, and applications with different kinds of objective functions as basis for planning; see e.g. [49] for a classical example using cost functions to maximize the sum of probabilities along paths. The same idea is extended in [4], using an objective function and Gaussian approximation techniques to relate the sampled and un-sampled locations, optimizing information gain along a 2D path. Also, this paper is one of a series of papers concerned with maximizing information gain from in-situ measurements, see e.g. [53, 50, 42]. Non-parametric optimization is explored in [51], where a self-adaptation path planning scheme for a glider is developed based on differential evolution algorithm, to achieve better tracking of sub-mesoscale eddies. Spatio-temporal dynamics are complicating the data-collection strategy. To address this, various models have been applied to estimate the change. Starting with compact ocean models, which have been used to guide AUV data collection in [1], and underwater gliders in [6]. However, current synthetic ocean models (see e.g. [8]) still lack the detail necessary for accurate predictions of change. Statistical prediction of surface currents using satellite data have also been suggested as an effective aid for underwater vehicles [17]. Others include, Markov based approaches, which have been used for ocean feature detection [22], and recently Markov Decision Processes (MDP) have been applied to produce path strategies for AUVs influenced by spatial and temporal uncertainty [23]. Building a semantic prediction of the environment, under spatio-temporal variation, is also explored in [18]. Focusing on modeling curiosity to elevate
the utility for long term missions with mobile robots, the algorithms are implemented in an under-water vehicle. In-situ identification of features using Gaussian Process Regression (GP) and supervised learning is presented in [9], aiming to select optimal sampling points, for an AUV with water sampling capabilities. The work presented here is explicitly related to the AUV domain. Research concerned with aerial and automotive application combine to a significant source of influence to the field, and should therefore be considered when examining the field of applied robotics, see e.g. [23].

Contributions

This review accounts for the work related to data-driven adaptation for AUV and marine robotics. Work published by groups relating to K. Rajan, J. Bellingham, M. Carreras, and G. Sukhatme have presented acclaimed work within autonomous planning the oceanographic context – much of the ideas and methods presented are attributed to their research effort. Theory related to Gaussian processes and spatial statistics have been adopted from Noel Cressie’s book "Statistics for Spatial Data", E. C. Rasmussen’s "Gaussian Processes for Machine Learning" and Jo Eidsvik’s book "Value of Information in the Earth Sciences", see [7, 35, 12].

Figure 2: AUV deployed under ice. Image courtesy of Woods Hole Oceanographic Institution (WHOI).
3 Ocean observation with AUV

Only a concise overview of ocean observation with AUV is presented here, referring the reader to the book by Mae L. Seto [2013] for a more in-depth review.

The first AUV arrived on the scene in 1957 [45], with development speeding up in the late 80s and 90s [2] as inertial navigation systems (INS), underwater communication and hardware technology (batteries, sensors, etc.) became better. The AUV has today become mandatory in ocean science and a variety of types are manufactured across the world; numbers from 2002 indicate 75 AUVs either under development or in operation [16]. Applications for AUVs are numerous, stretching from; offshore oil and gas, mineral exploration, military application, and in academic ocean science. Classic scientific operations include water column surveys [13] and bathymetric mapping [14, 48]. Operation below ice have also been explored, see e.g. [29, 15]. Common characteristics within scientific usage are; **large areas and prolonged/persistent time, with focus on data recovery**. Traveling in the ocean, the AUV must collects data whilst interacting with ocean forces – mainly currents, which can cause navigation error and gaps in data coverage [46]. Forces fluctuate over a wide range of temporal and spatial scales, from global variability to local small-scale episodic events [11]. In numbers, the dynamical landscape scale from 1km to 500km, and is divided into the following sub-scales:

- **Mesoscale**: 50-500km, 10-100 days.
- **Sub-Mesoscale**: 1-10km, days-months.
- **Rossby radius**: 10km.

The spatio-temporal variability observed in the ocean give rise to mesoscale and sub-mesoscale patchiness/structures – in which certain types (e.g. biomass) of information will tend to be clustered [24, 11]. The particular fluid flow structures are in oceanographic terms addressed as Lagrangian coherent structures (LCSs) [31]. To better apprehend the shape and intricacy, pictures of the surface current in Monterey Bay is presented in Figure 3a, together with algal blooms in the Baltic sea during spring, Figure 3b.

![Figure 3a: A Lagrangian Coherent Structure of surface current in Monterey Bay. Image courtesy of François Lekien (Université Libre de Bruxelles) and Chad Coulliette (Caltech).](image1)

![Figure 3b: Algal bloom inside the Baltic sea. Image courtesy of European Space Agency.](image2)
So what is the implication for ocean observation with AUV? The scales, at which the spatio-temporal variation is active, compared to the limited AUV(s) coverage capacity, imply that parts of the oceanic domain will be under-sampled. Being under-sampled means being below the Nyquist rate, which entail that the dynamics of the phenomena is not captured at a level capable of reconstructing the original distribution (aliasing). Observation with AUV must therefore not only consider where to sample, but also when to sample. Accordingly, it is important to identify the correct spatial and temporal scales at which to adequately quantify the process of interest. Spatial considerations can typically be demonstrated by considering AUVs used for water column surveys. In this context AUVs tend to be run in a yo-yo pattern (see Figure 5), traversing up and down with pitch angles from 10-28 degrees, in order to maximize the spatial resolution of the process, which generally is higher in the vertical, compared to the horizontal plane. Temporal considerations can be represented by an conceived example where an AUV having a maximum speed of 3 knots, cannot be expected to effectively resolve a phenomenon transporting information at the same speed – because it would never catch up with the data further ahead. Another factor important to note in this context is that the phenomena being considered is not always directly observable. Processes are often latent, only to be examinable by proxy variables (e.g. chlorophyll fluorescence, backscatter, temperature, salinity) [41, 33, 24]. Together with constraints on time, energy, sampling resources, robot actuation, and phenomenon uncertainty, the above mentioned elements constitute a sampling conundrum [33] in ocean exploration. Data collected at sea with AUV is therefore far from flawless often yielding only quasi-synoptic coverage [2]. To successfully respond to the dynamical features of the ocean, the AUV needs to be able to adapt its mission, while also cooperating with other sensor platforms.

Figure 4: Conceptual view of a multi-platform AUV field experiment.

2 Quasi-Synoptic – a non-holistic recording of an event.
The dynamic nature of the ocean as an argument for applying adaptive autonomy, can further be leveraged by looking at the ecosystem context, notice Figure 5. Detailed dynamics involving temperature changes (diurnal variation), biomass mobility, light conditions, and predator-prey interaction [30], to mention a few determinants, illustrate the significant role of the environment in the oceanographic domain. Having to resolve and interpret sensory signals to yield information about the surroundings in an ecosystem framework (feature recognition) is not trivial, but highly interdependent on collaboration with biologists/ecosystem experts, and is therefore a challenge that often is solved at a problem to problem basis. The non-concrete/fuzzy nature of these processes frequently require advanced classification techniques, adopted from machine intelligence, to decipher – relying heavily on statistics to extract information. Examples of work which address the theme of feature recognition with AUV is presented in [22, 9]. When dealing with in-situ identification, AUV sensor technology is essential for decoding the input from the physical environment, see e.g. [43] for a summary of relevant sensors. Sensor packages vary greatly among the different AUV types, which contribute to the notion of having to work out the environment on a problem to problem basis. In [48] new technological developments for AUV sensors are discussed in more detail. Altering the mission based on faulty data assimilation will misguide the AUV into sub-optimal regions for data collection. In short, describing and maintaining a correct view of the surroundings is vital for achieving effective adaptability, addressing the challenges in the preceding section.

Figure 5: Physical ocean forces and biological interaction. Image courtesy of Jayne Doucette (WHOI).

To reduce the shortcomings of one platform – i.e. lack of coverage, persistence, communication etc. – ocean observation seek to collect information from a range of sources, see Figure 4 on
the previous page. Integration, networks, and communication between these sources is a highly active research field, see e.g. [10] [32]. Below is a short summary of some of the technological components involved with the new adaptive, cooperative, and intelligent approach for AUVs and oceanography:

- **Satellites**: Using the electromagnetic spectrum (visible, infra-red, and microwave), satellites provide synoptic and large scale, high resolution, information [21]. From this; currents, plankton, temperature, sea levels, and waves can be asserted. Together with buoys and gliders, platforms with high persistence and good communication is often referred to as remote sensing platforms.

- **Giders**: Type of AUV based on motion from passive energy; typically buoyancy and currents are exploited in conjunction with some form of wing/foil to drive propulsion. Gliders are high persistence robots and can sample for long periods of time, forsaking mobility. They can be deployed on the surface or under water. One example of use is given in [19], where cooperation with AUVs have been demonstrated for helping the AUV "stay" with an identified advecting patch, letting the glider estimate the flow of the water masses.

- **ROV**: Remote Operated Vehicle – Self-propelled submersible whose operation is remotely controlled by an operator through an power and communication umbilical. Less mobile, these robots have been specialized for inspection and intervention activities, equipped with manipulator arms and tools. ROVs are beginning to incorporate more autonomy and is starting to look like AUVs in some characteristics [40]. Projects like SWARMS (http://www.swarms.eu/) aim to increase the cooperative mesh between AUVs and ROVs.

- **Buoys (moored sensors)**: Traditionally stationary, floating on the surface, but underwater and mobile versions exists (see gliders), provide persistent presence and can be deployed in a network. Instrumentation can be diverse depending on the application; no particular restrictions apply as long as the sensor can withstand water and weather.

- **UAV**: Unmanned Aerial Vehicle – Similar to satellites, flying drones can capture synoptic data, relay information, and give situational awareness to the AUV. Oceanic signature validation/detection has also been demonstrated on front detection and sunfish tracking; see e.g. [32].

- **USV**: Unmanned Surface Vehicle – Usually a ship-shaped vessel operating on the surface capable of data collection and relay. In contrast to a UAV, the USV can communicate both over and under water, accommodating both radio and acoustic communication equipment. Keeping contact with an AUV acoustically, while relaying AUV information to shore, is a typical application of an USV/AUV operation.

- **DUNE**: Refers to the Unified Navigational Environment. Onboard software for AUVs maintained by LSTS: Underwater Systems and Technology Laboratory, Porto, Portugal (http://lsts.pt/). It provides an operating-system and architecture independent platform abstraction layer, written in C++.

- **Neptus**: A networking and planning tool developed for integrated marine robotic operations by the University of Porto. See e.g. [10].

- **T-REX**: Telego-Reactive EXecutive – Onboard artificial intelligent agent architecture. Capable of automated planning (synthesized in-situ) and adaptive execution, aided by the temporal constraint-based planner EUROPA. EUROPA is developed by NASA, while T-REX has its origin from Monterey Bay Aquarium Research Institute (MBARI). For more
• **MOOS-IvP**: MOOS-IvP is a set of open source C++ modules for providing autonomy on robotic platforms, in particular autonomous marine vehicles. MOOS-IvP is based on multi-objective optimization.

• **ROS** – The Robot Operating System (ROS) is a set of software libraries and tools that help you build robot applications. Comparable to DUNE.

• **CTD - sensor**: Measures conductivity, temperature and density – CTD measurements are vital in oceanography and is therefore a crucial sensor onboard the AUV. Numerous properties can be extracted from these measurements, both directly and as a proxy for other parameters.

Figure 6: AUVs, ROVs, Gliders, USVs and buoys ready for deployment on cooperative type mission. Image courtesy: Katrina Ross UK Chamber of Shipping (2015).
4 Data-Driven Sampling with AUV

Overcoming the drawbacks inherited by conventional survey strategies can be resolved by allowing the AUV to use collected information – hence the phrase "data-driven" – to adapt its mission accordingly. The ability to do more advanced surveys, reduce mission duration, and the amount of redundant data collected, motivate the use of more advanced control strategies. Incorporating adaptive algorithms into mobile agents have been researched extensively and several approaches have been investigated, see e.g. [9, 33, 19, 16, 46]. The ability to adjust execution on the basis of sensory information is a problem not just in robotics, but also statistics, geology, atmospheric science, and other fields concerned with optimizing information gathering. In these domains – characterized by limited sampling resources – intensive sampling of the relevant regions is too expensive and hence need to rely on adaptive sampling methods to provide the best possible coverage. This review propose a generic cycle for explaining the different dependencies within adaptive/data-driven sampling, divided into: Prior prediction / information → Data collection → Data assimilation → Generate sensing strategy. The overall goal with the system is to effectively fuse observation updates with prior knowledge on which subsequent decisions are made to improve the data collection strategy. Building a flexible framework that can learn/adapt on its own is critical, since we can only specify what little we know in advance, which almost certainly will be incomplete – reverberating what was emphasized in the introduction.

Figure 7 illustrate the steps involved in data-driven sampling, starting at the top with – the world model. The world model can be compared to a knowledge base that incorporate all information about the environment. This typically includes the initial states, model description and representation, and environmental expertise relevant for the mission domain. Depending on the application and implementation choice, different declarative representations are used to serve varying functional requirements (e.g. path planning, collision avoidance, cooperative planning, etc.). Generally the knowledge is contained in a practical searchable data structure having some from of state representation; often complemented by a continuous or grided map of the environment used for path inference. Some typical representations are; potential fields, statistical and parametric models, roadmaps, and value based grids. The current world state representation act as a workspace across the different components of an autonomous agent – e.g. navigator and planner can both access the map structure for waypoint inference. A vital function is the storing and updating experience during mission execution. This is generally solved by defining an initial state and do state estimation to keep track of world evolution as time advances, based on the declarative model of choice. Section 4.1 provide an example using a Gaussian process model (GPM).

Returning to Figure 7, we start with a predefined data collection plan/policy originating from a prior prediction/model. Starting without any predefined plan is of course possible, leaving all planning to the agent, but is not often practical. Typically a set of waypoints is selected and used as "lead in" for the agent, chosen as a best guess optimal launch route. Despite being based on scientific expertise, the degree of discrepancy will likely be large for early points of comparison with the predicted world state. The risk of confusion and long-term sub-optimal performance is therefore high in early phases of deployment. This is typical when the effective number of observations are small, since the bias is much larger than the variance in the beginning, dominating the mean-square error.

Retaining an advantageous strategy for information recovery, which is the entire point of using a data-driven agent, require a favorable reconciliation of recovered data with the world model, continuously adding and refining current knowledge. Consequently, Data assimilation must run
in parallel, fusing information in such a way that prosperous behavior is maintained. This can be performed in numerous ways, but usually consist of a statistical update procedure; often based on Bayesian approaches i.e. Kalman-filtering, Gaussian process (GP) updates [9], or Markovian transmission matrix updates [25], to mention a few. The generated posterior belief is then integrated with the current world model, yielding an updated and, hopefully, improved conception of the environmental state/world evolution – "Model assimilation" in Figure 7. In the strict sense of the word, knowledge can only be about the past, and the environment can in certain situations change faster than the agent can plan. However, given that the process is observable and the notion that the future largely is being made out of existing material a reasonable estimation of the world state can be made. Or said in a different way – a proper understanding of the current situation, can help in the formation of a sound judgment for the future. Once a new world state is available, the strategy for information recovery can be re-evaluated and potentially refined – the last step in Figure 7 "Generate sensing strategy".

Formulation, or refinement, of a data-driven plan is a complex task, much due to the fact that

3Often referred to as a Markov property, implicating that the future state depends only on the present state.
a compromise has to be found between a set of objectives and constraints, whilst finding agree-
ment with the entities already integrated into the plan. Complications such as; resource lim-
itations (e.g. balance between sensor coverage and battery life), competing objectives/goals,
off-nominal conditions, fault tolerance, and synchronization has to be settled according to some
from of computational understanding built into the agent reasoning/planning system. Different
approaches that have been explored for AUVs can be found in [41], including; AI based planners
[27], objective optimization schemes [3], and gradient based methods [49, 4]. The inferential
mechanism (decision-making cycle) at work need to balance world state exploration (opportunist-
ically following features of scientific interest), and exploitation (providing a goal focus in action
selection/planning). Another challenge for computational planning is the concern of problem
scalability and computational limitations. Due to this, most planners incorporate some form
of planning horizon, on which re-evaluation and adaptation can be invoked, ensuring adequate
external responsiveness.

4.1 Data-Driven Sampling using a Gaussian Processes

To illustrate how these ideas can be practically applied, an example using Gaussian processes and
Kriging, to update the world evolution, is demonstrated in this section, by looking at an upper
water column survey with a single AUV. Before the concrete example is presented, it is necessary
to define some background theory concerning Gaussian processes and spatial interpolation using
Kriging. For a more rigorous introduction to the theory of GPs, see [35] or [7].

4.1.1 GPs and Interpolation with Kriging in a Oceanographic Context.

GPs are an important tool in probabilistic modeling with a broad range of applications and
have been used extensively to model natural processes, due to the fact that the distributions
of many natural phenomena are at least approximately normally distributed [4]. Working with
GPs provide analytical simplicity, since a finite subset of GP generated data, located throughout
some domain, will follow a multivariate Gaussian distribution. Hence, the transmission from a
Gaussian process to a multivariate Gaussian distribution is seamless, more formally:

**Definition 1.** A Gaussian process is a collection of random variables, any finite number of which
have (consistent) joint Gaussian distributions.

Additionally, the GP is completely defined by its mean and covariance function. A GP is a
special type of stochastic process/random function (the terms are used interchangeably), where
the set of random functions studied have certain measure of "smoothness", inherited from the
specification of the correlation between the values of the function. GPs is therefore, in many
respects, closely related to the study of covariance functions (also known as a kernel function).
A typical problem with sparsely sampled environments is to estimate the value at unobserved
locations, in order to arrive at the synoptic view necessary for planning. Kriging is a method
of interpolation, widely used in spatial analysis, originating from geo-statistics and named after
Danie G. Krige which first used it for estimating deposits for gold. Together with ordinary
least squares (OLS), Kriging derive the best linear unbiased prediction of the values at the

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4This follows from the central limit theorem, stating that; for statistically independent samples, the probability
distribution of the sample mean tends to become Gaussian as the number of statistically independent samples
increase, regardless of the probability distribution of the random variable or process being sampled, as long as it
has a finite mean and a finite variance.
unobserved locations [44, 7]. The interpolated values are obtained using predictions delivered from the covariance functions; predicting the functional value at a given point by a weighted average of the values in the neighborhood of the point – it is important to note that the optimal estimate at a unobserved location is a linear combination of the observed values, where we do not want to trust each proximal point equally in our analysis.

Starting with a GP model as a prior, a specified covariance function is defined by a given set of hyperparameters [44] providing the spatial relation between to points in the GP. In addition, the covariance function has to be positive definite. A set of observations is then made, as a location value pair, which can render new values at any location in the specified GP, by assimilating with the GP prior to produce an updated GP posterior. Different methods of Kriging exists, depending on the stationary properties, characterizing the comparability dynamics (covariance description), of the random field. In this context the notion of isotropy is important to note. A covariance function which is isotropic, is invariant to translations in the input space; only being a function of \( ||s - s'|| \), where \( s - s' \) is a distance metric. Isotropy is required for the random field to be stationary or weakly stationary, which is explain in detail below.

The spatio-temporal dynamics of the ocean introduce multi-dimensional (time and space) uncertainty relating to the latent process. The choice of a GP description is a strategic one for the spatial case, which can be assessed by investigating the variogram; providing a analytical approach for assessing the spatial dependency. Tempting as it may be to compare the spatial and temporal dependence between points, only a comparison by contrast is possible. Since the time varying uncertainty cannot be integrated directly with a GP, without weakening the underlying properties for GPs; assuming the process is stationary or even weakly stationary [45]. The temporal dependence of the latent process for integration into GPs, must therefore be resolved by: assuming approximate stationarity for a finite horizon, using corrective measures to estimate the time dependent dynamics, or even ignoring time variation completely.

4.1.2 GP Modeling

A Gaussian process is fully defined by its mean function \( m(s) \) and covariance function \( k(s, s') \equiv \text{Cov}(f(s), f(s')) \) at location \( s = (\text{east}, \text{north}) \), which is a generalization of the Gaussian distribution defined by the mean vector \( \mu \) and the covariance matrix \( \Sigma \). Following the notation given in [55], a function \( f \) distributed as a GP can be written:

\[
f = \mathcal{GP}(m, k)
\]  

Once we have chosen \( f \) as the descriptive function, we start by modeling a GP prior from a training data; in this case a numerical model. A snapshot of the calculated surface temperature outside the coastal region of Froan is presented in Figure 9b. The mean function \( m(s) \) is found using multiple linear regression on this temperature data, see Figure 9a, yielding the resulting \( \beta \)-vector=[5.42 0.0026 0.0057]. The covariance function \( k(s, s') \) is set to the squared exponential kernel. Consider then the Gaussian process given by (1) and;

\[\text{Learned covariance adjustment parameters, expressing the belief about how functional values can covariance.}\]

\[\text{In stochastic process theory a process which has constant mean and whose covariance function is invariant to translations is called weakly stationary. A process is strictly stationary if all of its finite dimensional distributions are invariant to translations.}\]
\[ m(s) = \beta s = 5.42 + 0.0026 e + 0.0057 n, \]
\[ k(s, s') = \sigma^2 \exp(-\gamma ||s - s'||), \]

where \( s \) is the location tuple \( s = (\text{east}, \text{north}) \), \( \beta \) is the regressed mean vector, \( \sigma \) and \( \gamma \) are covariance design parameters (hyperparameters), and \( ||s - s'|| \) may be recognized as the Euclidean distance between point \( s \) and \( s' \). To obtain the correct correlation range, a variogram analysis of the surface temperature indicate a correlation distance of approx. 7km, for this particular temperature realization. The variogram is displayed in Figure 8b together with the predicted values for \( \mu \), in Figure 8a.

![Figure 8: (a) The prior predicted values for the GP realization, before any observations are made. (b) The variogram for the ocean surface temperature.](image)

This prediction constitute the world model, referring to Figure 7. Once this is established the AUV in the example is deployed and data-collection can start.

### 4.1.3 Updating the GP with Observations

In order to capitalize on observations, sensory information have to be fused with our estimated prior to attain a posterior GP. Let \( f \) be the known function values at \( s \), based on temperature data at 5m depth from a pre-calculated numerical model (prior), and \( f^* \) be the temperature values collected at location \( s^* \).

\[
\begin{pmatrix}
f \\
f^*
\end{pmatrix} \sim \mathcal{N} \left( \begin{pmatrix}
\mu \\
\mu^*
\end{pmatrix}, \begin{pmatrix}
\Sigma & \Sigma_{s*} \\
\Sigma_{*s} & \Sigma_{**}
\end{pmatrix} \right),
\]

\[\text{A variogram is a plot which is constructed to help relate the spatial distance between points with the points variance. Typically as the distance increase, the variance increase, until a limit is reached. At this limit the points no longer yield any relation based on the data value and the variance can no longer grow.}\]
where $\mu = m(s_i), \ i = 1,...,n$ for the $n$ prior locations, and analogously $\mu^* = m(s_k), \ k = 1,...,p$ for $p$ collected observations, $\Sigma$ is the covariance matrix between locations in $s, \Sigma_s$ the covariance matrix between $s$ and $s^*$, and $\Sigma_{ss}$ is the covariance matrix for the observed locations $s^*$; the full expression for the covariances matrices can be found in [35]. Note that the predicted values at the unobserved locations is a linear combination. Knowing the values of $f$, the conditional joint Gaussian distribution for $f^*$ is expressed as:

$$f^* | f \sim N(\mu^* + \Sigma^\top_\ast \Sigma^{-1}_s (f - \mu), \Sigma_{ss} - \Sigma^\top_\ast \Sigma^{-1}_s \Sigma_s).$$

(5)

The corresponding posterior process is:

$$f|D \sim GP(m_D, k_D),$$

(6)

$$m_D(s) = m(s) + \Sigma^\top_s \Sigma^{-1}_s (f - \mu),$$

(7)

$$k_D(s, s') = k(s, s') - \Sigma^\top_\ast \Sigma^{-1}_s \Sigma_s,$$

(8)

where $m$ is the prior temperature prediction at the sampled locations $s^*$. Note that the posterior covariance $k_D(s, s')$ is reduced in comparison to the prior covariance, since the updated equation subtracts an always positive term $(\Sigma^\top_\ast \Sigma^{-1}_s \Sigma_s)$ representing the additional information gained from adding the new observations. Another factor which is important to notice is that the GP update requires inversion of the covariance matrix $\Sigma$, which can be computationally expensive. Due to this drawback, a large body of research revolves around finding solutions to this issue inherited to GPs. The update results can be seen in Figure 9. The sampled locations are shown as crosses in Figure 9b, illustrating the AUV path. Using the data collected along this line the GP is updated according to equations (6)-(8), to obtain the posterior GP in Figure 9c.
Temperature Regression Estimate

(a) Regression of temperature.

True underlying process

(b) True underlying process.

Posterior Prediction

(c) Posterior prediction of Gaussian Process.

Standard Deviation

(d) Standard deviation estimation error.

Figure 9: Updating a GP model using measurements from AUV.

The standard deviation in Figure 9d is small along the AUV observation sites (only sensor noise), and gradually increases to the level of the process noise as one gets further from the actual measurement site. Interpreting the updated GP – also known as the Kriging prediction – in Figure 9c may not impress the reader much, as the level of change can seem limited. A side by side comparison with sharper color – to better see the result of the prediction – can be seen below:
Due to the nature of Kriging—interpolation based on covariance—two values that are nearby will not contribute twice the information, as the two values are highly correlated, the data will be redundant. Based on the modeling assumptions, the new prediction is also Gaussian, with the variance independent by the actual measured data; only the spatial dependencies between the data [12] is important.

In this example we have seen a method using GPs to hold and capture data, maintaining a non-analytical environmental model of the estimated ocean temperature at 5m depth. The predicted temperature distribution can now be used as input into the subsequent sensing strategy, enabling adaptation to observed changes during mission deployment. A full implementation of a GP based world model approach, would include additional predictions to complete the environmental description. For AUVs equipped with CTD’s, a natural starting point would be to have depth specific predictions of both temperature and salinity. This is of great use for upper water column surveys with AUV, in order to assess water body interaction phenomenon such as frontal systems.

4.1.4 Adaptive Sampling Strategy for Fronts

To illustrate the full cycle of data-driven sampling, a short adaptive application, using the developed GP model, is presented, where the AUV is to localize and track a temperature front. The GP prediction is used together with a k-means algorithm to segment the temperature field into two groups, which are then used as the estimate of the interface between the two water bodies. This constitute a significant simplification. However, this shortcoming is accepted for the sake of the example. In Figure 11 the different steps involved are shown:

---

*A volume of water with such clear properties (i.e. temperature and salinity) that it can be distinguished from other volumes of water.*
The GP provide an updated data-driven prediction of the temperature field, Figure 11b. This is then fed into a k-means algorithm which split the GP into two groups according to the temperature distribution, see Figure 11c. The interface is then extracted (red line) and a zig-zag path is calculated (green path) and fed into a simple guidance controller, driving the AUV through these adaptive waypoints. As the AUV is traversing the field, collecting data, the temperature front will change according to the newly acquired information, as well as the waypoints and zig-zag path. Hence, the waypoints are non-static. A simulation example with this approach is shown in Figure 12.

Figure 12 shows the five list predictions of the interface. The AUV path is updated each time the AUV reach a new waypoint, the corresponding path can be seen as the black dashed line in Figure 12a along with the frontal interfaces superimposed on the true underlying temperature field. The goal of the adaptive system (GP model and adaptive algorithm) is to dynamically track the front between the two water masses, the front location belief state, captured by the k-means
prediction, is more functional for a search type modulus within the adaptive agent. In practice, once the actual front is crossed –measuring a gradient event change with the CTD– the concrete front location is obtained. This location can then be used directly for path inference without consulting the k-means prediction. However, should the AUV lose track of the front later, the k-means prediction provide and best guess to where to start searching. A actual implementation of a frontal tracking control will therefore likely be a combination of search mode and tracking mode.

5 Conclusions and Future Work

A proof of concept, using adaptive sampling based on GPs, have been shown in Section 4.1, this constitute a solution to some of the challenges discussed in Section 1 and 3, but much work remains to attain a reliable and trustworthy autonomy layer.

Work related to the static assumptions within GP covariance functions is critical for the credibility of the exemplified approach in Section 4.1.3. Having an analytical approach for the spatial dependency by means of variogram analysis, a study of the time dependency of covariance functions for oceanographic dynamics is necessary to increase predictive performance. As mentioned, the temporal dependence of the latent process, have previously been resolved by; assuming approximate stationarity for a finite horizon, using corrective measures to estimate the time dependent dynamics, or even ignoring time variation completely. The challenge is to reduce the temporal uncertainty in the input data to the path planner, so that data-collection can account for the time variation of the process. Also, support and collaboration with other platforms, capable of more synoptic data coverage, can help resolve dynamics that are hard to predict from an AUV perspective.

Further work needs to be done going from a GP representation to explicit detection of physical ocean forces and ecological features. Using a set of carefully selected covariates; such as oxygen content, watercolor, cooperative measurements, water depth, etc., together with the GP can be one solution, see Appendix B for an example developing a covariate function. The k-means approach shown in the preceding example can be used for search, but is considered too brute for precision tracking once the front is detected. Augmentation using covariates can also here be used to refine the estimate. Testing and verification of this coming work can be evaluated using numerical oceanographic models like SINMOD, providing a virtual ocean for AUV control strategies. Advancing the predictive capacity of oceanographic models can in this regard have significant influence on AUV autonomy, emphasizing that collaborative work between these two disciplines have considerable value for both parts.
References


[26] MBARI. Canon: Controlled, agile and novel observing network (research program). In [MBARI Online Resource].


A Overview of different AUV classes

Tables are courtesy of Zheng Zeng 2015.

Table 1
Category I-Long Range AUV (Endurance > 72 h).

<table>
<thead>
<tr>
<th>Name</th>
<th>Manufacture</th>
<th>Size [LxWxH]</th>
<th>Weight</th>
<th>Depth</th>
<th>Speed</th>
<th>Energy</th>
<th>Endurance</th>
<th>Figure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autonomy long range</td>
<td>National oceanography centre</td>
<td>3.68 m x 0.90 m x 0.90 m</td>
<td>600 kg</td>
<td>6000 m</td>
<td>0.8 m/s</td>
<td>16.9 kW h</td>
<td>440 h</td>
<td><img src="image1.png" alt="Image" /></td>
</tr>
<tr>
<td>Tethys (Hobson et al., 2012)</td>
<td>MBARI</td>
<td>2.30 m x 0.31 m x 0.31 m</td>
<td>190 kg</td>
<td>200 m</td>
<td>0.3 m/s</td>
<td>Information not available</td>
<td>740 h</td>
<td><img src="image2.png" alt="Image" /></td>
</tr>
<tr>
<td>Reliant (Navy·Mine·Hunter·AUV Sets Mission Endurance Record)</td>
<td>U.S. Naval research laboratory's (NRU) &amp; bluefin robotics</td>
<td>6.1 m x 0.53 m x 0.53 m</td>
<td>612 kg</td>
<td>4500 m</td>
<td>1.28 m/s</td>
<td>40 kWh</td>
<td>109 h</td>
<td><img src="image3.png" alt="Image" /></td>
</tr>
</tbody>
</table>

Table 2
Category B-Medium Range AUV (24 h < Endurance < 72 h).

<table>
<thead>
<tr>
<th>Name</th>
<th>Manufacture</th>
<th>Size [LxWxH]</th>
<th>Weight</th>
<th>Depth</th>
<th>Speed</th>
<th>Energy</th>
<th>Endurance</th>
<th>Figure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autonomy6000 (Griffiths and Norhall, 2011)</td>
<td>National oceanography centre</td>
<td>5.50 m x 0.90 m x 0.90 m</td>
<td>2000 kg</td>
<td>6000 m</td>
<td>1.0 m/s</td>
<td>4.5 kW h</td>
<td>70 h</td>
<td><img src="image4.png" alt="Image" /></td>
</tr>
<tr>
<td>Remus 600 (Stokey et al., 2005)</td>
<td>Hydroid</td>
<td>4.27 m x 0.32 m x 0.12 m</td>
<td>326 kg</td>
<td>600 m</td>
<td>1.5 m/s</td>
<td>5.2 kW h</td>
<td>50 h</td>
<td><img src="image5.png" alt="Image" /></td>
</tr>
<tr>
<td>Bluefin-12 (Taylor and Wilby, 2011)</td>
<td>Bluefin robotics</td>
<td>3.77 m x 0.32 m x 0.12 m</td>
<td>284 kg</td>
<td>200 m</td>
<td>1.5 m/s</td>
<td>4.5 kW h</td>
<td>26 h</td>
<td><img src="image6.png" alt="Image" /></td>
</tr>
<tr>
<td>Bluefin-21 (Bluefin Robotics)</td>
<td>Bluefin robotics</td>
<td>4.10 m x 0.53 m x 0.53 m</td>
<td>525 kg</td>
<td>4500 m</td>
<td>1.5 m/s</td>
<td>13.5 kW h</td>
<td>25 h</td>
<td><img src="image7.png" alt="Image" /></td>
</tr>
<tr>
<td>Hugin 5000 (Hagen et al., 2005)</td>
<td>Kongshavn maritime</td>
<td>4.70 m x 0.75 m x 0.75 m</td>
<td>850 kg</td>
<td>3000 m</td>
<td>2.0 m/s</td>
<td>15 kW h</td>
<td>24 h</td>
<td><img src="image8.png" alt="Image" /></td>
</tr>
<tr>
<td>Name</td>
<td>Manufacture</td>
<td>Size (LxWxH)</td>
<td>Weight</td>
<td>Depth</td>
<td>Speed</td>
<td>Energy</td>
<td>Endurance</td>
<td>Figure</td>
</tr>
<tr>
<td>-----------------------------</td>
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</tr>
</tbody>
</table>
| MUNIN (Autonomous underwater vehicle - MUNIN AUV) | Kongsberg maritime | 0.30 m × 0.03 m × 0.03 m | 300 kg | 1500 m | 2.05 m/s | 5 kW h  | 22 h     | ![MUNIN AUV](image)
| Bluefin-9 (Bluefin Robotics - Bluefin Robotics)    | Bluefin robotics            | 1.65 m × 0.24 m × 0.24 m | 50 kg  | 200 m  | 1.52 m/s | 1.5 kW h | 12 h     | ![Bluefin-9](image)
| Iver2 (Incze, 2011)        | Ocean server technology     | 0.13 m × 0.01 m × 0.01 m | 19 kg  | 100 m  | 1.29 m/s | 0.6 kW h | 12 h     | ![Iver2](image)
| Remus 100 (Nygard, 2014)   | Hydroid                     | 1.84 m × 0.19 m × 0.19 m | 45 kg  | 100 m  | 2.3 m/s  | 1 kW h   | 10 h     | ![Remus 100](image)
| Teledyne Cobia              | Gavia defence               | 1.80 m × 0.20 m × 0.30 m | 49 kg  | 1000 m | 1.00 m/s | 1.2 kW h | 7 h      | ![Teledyne Cobia](image) |
B  Development of a Heuristic Covariate Function

A short example of how to develop a covariate function which can help attaining a better assumption basis for GP modeling in the ocean is presented. The function is a heuristic based on combining clustering algorithms with histograms to extract underlying dynamics from numerical simulations. As illustrated in Figure 13 assuming two independent water bodies interacting, a snapshot of the two temperature regions can be used to classify each grid cell with the property of belonging to either water body 1 or 2. Water body 1 is given a bucket value of -1, while water body 2 is given bucket value of 1. As the temperature regions shift (when a new snapshot is evaluated), so does the attributed bucket value, hence a count of the class of water body is attained as time progresses.

![Figure 13: Steps involved when generating a cluster histogram.](image)

Once all snapshots have been split into water body 1 or 2, and the following grid cells have summed up the total sum of -1, or 1, the following output is obtained:

![Figure 14: Cluster histogram for survey area.](image)

The integration of the covariate function is relative straightforward, since each cell has a confidence value corresponding to the probable water body class at the current location.