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A Bayesian approach for predicting risk of autonomous underwater vehicle loss during their missions

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ABSTRACT

Autonomous Underwater Vehicles (AUVs) are effective platforms for science research and monitoring, and for military and commercial data-gathering purposes. However, there is an inevitable risk of loss during any mission. Quantifying the risk of loss is complex, due to the combination of vehicle reliability and environmental factors, and cannot be determined through analytical means alone. An alternative approach – formal expert judgment – is a time-consuming process; consequently a method is needed to broaden the applicability of judgments beyond the narrow confines of an elicitation for a defined environment. We propose and explore a solution founded on a Bayesian Belief Network (BBN), where the results of the expert judgment elicitation are taken as the initial prior probability of loss due to failure. The network topology captures the causal effects of the environment separately on the vehicle and on the support platform, and combines these to produce an updated probability of loss due to failure. An extended version of the Kaplan–Meier estimator is then used to update the mission risk profile with travelled distance. Sensitivity analysis of the BBN is presented and a case study of Autosub3 AUV deployment in the Amundsen Sea is discussed in detail.

1. Introduction

Autonomous Underwater Vehicles (AUVs) have a future as effective platforms for science research and monitoring, and for military and commercial data-gathering purposes. Increasingly they are being used in environments that are not benign [1,2]. Environments such as under sea ice [3], under shelf ice [4], or along rocky coasts [5] intuitively give rise to a higher risk of loss should the vehicle malfunction. The risk of loss is real; for example, Australian and British AUVs have been lost under ice sheets [6] and one team maintained a lightweight tether to an AUV when operating under sea ice. The problem of predicting risk of loss is not only one of predicting the reliability of the vehicle as a whole, its sub-systems and its components, but also of how the operating environment, together with reliability, sets the probability of losing the vehicle. It is not obvious that an approach based on separate statistical analyses of vehicle reliability and the affects of the environment on probability of loss is either feasible or meaningful. Such an approach, when reduced to summary statistics such as mean time to failure, would ignore the interaction between individual faults or incidents and the environment, which we postulate to be at the centre of this problem.

One alternative would be to assess the probability of loss in various environments directly, by counting the frequency of occurrence. This frequentist approach is certainly appropriate for assessing the reliability of identical engineered systems, where probability of failure is derived from a long-run frequency of occurrence, usually from the study of many items in use. Such an approach is the foundation for general reliability handbooks [7]. This is also the approach taken for obtaining reliability statistics in the offshore industry, for example the OREDA database [8], first published in 1984 [9]. However, this methodology “does not give the designer or manufacturer any insight into, or control over, the actual causes of failure since the cause-and-effect relationships impacting reliability are not captured” [10]. It is precisely that cause-and-effect between vehicle fault or incident and the environment that we seek to establish.

In [11], the authors present a risk management process tailored to AUV deployment in extreme environments. The method was used to support the decision to deploy the Autosub 3 AUV underneath an ice shelf, the Pine Island Glacier, Amundsen Sea, Antarctica in 2009 and again in 2013 [12]. Expert judgment was sought to quantify the likelihood of loss given a fault, and the experts' supporting text provided insights into possible causes and effects. The expert judgments were aggregated using mathematical analytical methods

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In contrast to the simple, yet high risk, case of AUV operation under an ice shelf, operations in other environments pose more complex risk scenarios, examples include under sea ice and coastal operations. Furthermore, the risk is often modified by the characteristics of the support platform. There is a set of AUV mission circumstances, therefore, where the range of factors is sufficiently large that it would be impracticable to ask an expert panel to review and assess every possibility. A method is needed to estimate risk under different conditions that minimizes the call on external experts, yet is well founded on their judgments.

We propose a three-stage approach to predicting risk of loss of an AUV during a mission in an environment that is different from that agreed as the nominal conditions. The first stage uses the formal process of eliciting expert judgment to quantify the likelihood of each failure leading to loss under a set of nominal conditions [13–15].

The second stage generalizes the experts' judgments to a new operating environment. For this stage a solution founded on a Bayesian Belief Network (BBN) approach [16] is proposed as it is an accepted method for modelling complex probability problems where it is possible to establish a causal relationship between domain variables [17,18]. The design of the network topology captures the causal effects of the environment separately on the vehicle and on the support platform (e.g. a ship), and combines these to produce the output. For our example environment of under sea ice, we use the ASPeCt sea ice characterization protocol [19] and probability distributions of ice thickness and concentration within a rigorous process to quantify risk given a range of sea ice conditions and with ships of differing ice capabilities. Complementary expert knowledge is included within the conditional probability tables of the BBN. In [20] we showed how a BBN model can be combined with Monte-Carlo simulation to generate risk 'envelopes' for the AUV operation. The role of the BBN here was to update cumulative risk distributions for a given operational environment. This cumulative distribution would then be integrated in a Monte-Carlo framework to randomly generate Kaplan–Meier survival plots of the AUV survivability with distance. This approach ignored the criticality of specific faults. A fault that was once considered of high criticality could later be deemed of low criticality and vice-versa. The approach presented in this paper is a significant improvement on previous work because instead of using the BBN for updating the cumulative risk profile for a given environment and operational constraints we show how the BBN can be used for updating the likelihood of loss for a failure for a given environment and operational conditions. This required fine-tuning of the conditional probability tables.

In the third stage, the extended Kaplan–Meier estimator is used for updating the risk profile in light of the revised probability of loss given failure.

2. Autonomous Underwater Vehicle risk modelling and analysis for extreme environment missions

Our Autonomous Underwater Vehicle risk model is based on the vehicle's intrinsic failure history and expert judgments on the impacts of failure in the target operating environment. As subjective probability is a belief assessment on the likelihood of a hypothesis being true, this will differ between individuals when the uncertainty is epistemic, that is, due to imperfect knowledge. There remains controversy among statisticians over the validity of subjective probability, between the frequentists and the adherents of Bayes' theorem [13]. However, O'Hagan and colleagues argue that "this controversy does not arise" for the practical elicitation of subjective probability [13]. Hence, in this work a formal process of eliciting expert judgment was followed [21].

2.1. Nominal risk models for open waters, coastal waters, sea ice and ice shelf

Several formal expert judgment elicitation methods have been developed over the years [14]. For this work, we draw upon the formal expert judgment elicitation that was conducted in order to build the risk model for Autosub 3 deployment underneath the Pine Island Glacier. The static risk model was based on expert judgment on the criticality of each failure in the failure history [21,22]. The subsequent analysis sought to identify biases arising from various causes [21,23]. When making probability assessments, people tend to follow a number of mental shortcuts, denoted as heuristics, these may be based on how quickly the occurrence of an identical event comes to mind, or the impact of the event or how one anchors his or her assessment to a known event. Representativeness, availability and anchoring are the most common type of heuristics. Research has shown that people can introduce biases when following heuristics [23,24].

Reference cases for risk of loss in different environments were obtained from an earlier study in which ten independent experts were asked to consider the simple question, "What is the probability of loss of the Autosub3 AUV in the given environment X given the fault/incident Y?" [14]. X comprised four example environments: open water, coastal, under sea ice, under ice shelf and Y comprised the set of 63 faults/incidents recorded on 29 missions to April 2007; 10 missions had no faults or incidents. The experts, from the USA, Canada and Australia, had a wide range of backgrounds, encompassing academic research (two graduate students and two full professors, both with polar experience, working on AUVs), research laboratories (three experts, two with polar experience), military research and development (two experts), and industry (one expert, with polar experience).

The full results are contained in a detailed 198-page report, available online [15], which contains nearly 2000 individual judgments, together with the expert's own assessment of their confidence in making each judgement. The authors augment the experts' reasons for their judgments with a commentary on points of agreement and disagreement, and conclude that where there were bimodal distributions, the experts seem to have fallen into two camps—optimists and pessimists. While noting these differences of opinion, the overall aggregated outcome was formed using a linear opinion pool for each fault or incident [21]. The final results were visualized as relative frequency distributions for the assigned probabilities for each environment (Fig. 1).

In reaching their judgments on the risk when operating in these four environments the experts were provided with brief descriptions of the characteristics of each environment that affect risk of loss. However, each expert also drew on their own knowledge of the operating environments, and in the supporting comments to their judgements gave reasons for reaching their probability of loss estimate for each fault. Rather than mathematically aggregating these judgements into a single probability of loss in each environment, which would over-simplify the assessment, and give a false sense of confidence, Fig. 1 shows the probability frequency distribution for each environment from the judgements of the experts.

For sea ice, the experts were asked to keep in mind an area of first year ice (0.3–2.0 m thick), 50% ice concentration, with ice keels to 15 m, sporadic icebergs and a ship capable of breaking 2 m ice at 2 kt. These parameters form the particular reference case – the prior information for the Bayesian approach – for the motivating example in this study. To help extend the risk modelling to other ice conditions, the experts' judgments on risk in open water and under ice shelf are important. In the Bayesian sense they provide new information as they bound the risks under the two extremes of sea ice conditions. Where there is a high fraction of open water between the sea ice, the risk should tend to that of