Evaluation of risk of loss an underwater Glider in the sea using BBN

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Resumen

Actualmente, la literatura relacionada con el desplazamiento y el control de trayectorias de vehículos submarinos está relacionada con los aspectos de autonomía del control de imágenes, planes de navegación, control avanzado, en los que estos sistemas se relacionan con vehículos autónomos submarinos. A continuación se muestra un análisis para conocer en la práctica el riesgo de perder un sistema submarino Glider (GUS) en el océano y para asegurarse de que siempre regrese a su punto de lanzamiento, un módulo de aprendizaje basado en una red de creencias bayesianas que fue diseñado para el robot en sí mismo que puede tomar decisiones sobre su navegación y autonomía. Además, se mostró la Bayesian Belief Network, con sus parámetros de diseño, basados en la capacitación, su efectividad y eficiencia.

Palabras clave—Vehículo submarino autónomo,Red de creencias bayesianas, Inferencia bayesiana, Sistema oceánicos no tripulados, AUV, GUS.

Abstract

Currently, the literature related to the displacement and control of trajectories of underwater vehicles is related to the autonomy aspects of image control, navigation plans, advanced control, in which these systems related to autonomous underwater vehicles. Below is an analysis to know in practice the risk of losing a Glider (GUS) submarine system in the ocean and to ensure that you always return to your launch point, a learning module based on a Bayesian belief network that It was designed for the robot itself that can make decisions about its navigation and autonomy. In addition, the Bayesian Belief Network was shown, with its design parameters, based on training, its effectiveness and efficiency.

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Keywords— *Autonomous underwater vehicle, Bayesian Belief Network, Bayesian inference, Unmanned oceanic frameworks, AUV, GUS.*

1. INTRODUCTION

Many researchers have tried to know better the ocean and its depths in order to know the relationship with the climate, the food resources it contains, the amount of fauna and flora of its environment. Several works in the literature have focused on the search and rescue of shipwrecks [1], discovery of new species [2], knowledge of the depths [3], preservation of the environment [4], pollution [5].

These motivations become necessities that require new technological developments to reach them, from them, it has developed in the specific nautical sector and telecommunications based on static and dynamic systems such as, buoys, Autonomous underwater vehicles (AUV) and Gliders. They try to reach all corners of the ocean to cover all these needs. An AUV is a robot that travels underwater, and its control underwater can be automatic or partially automatic through some communications link.

However, a particular group of the AUVs are the Glider underwater systems (GUS), which have no control capacity because they move with the marine currents. These vehicles have revolutionized marine exploration, obtaining more information, in greater depth and more extreme environments, with more safety for personnel and at a lower cost.

The Gliders are designed to have a relatively small positive buoyancy, so that with a small ballast tank (or piston) and the help of fins the vehicle is submerged changing its buoyancy, i.e. from positive to negative due to the weight gain of the liquid shipped on the piston. When the robot is submerged, the position of the fins converts the vertical vector into horizontal movement in movement. This movement typically is cyclical, so the vehicle is submerging and emerging continuously making wave trajectories, and one could say that it plans.

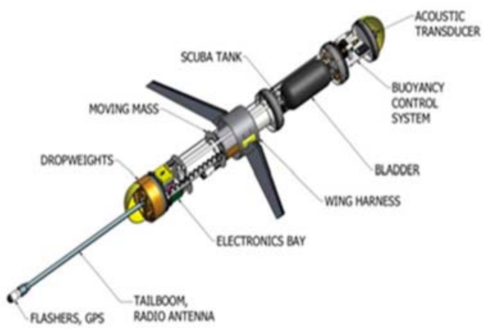
The vehicle moves slowly allowing itself to be dragged by the marine currents while it is taking information with its sensors of the environment. Each time the vehicle emerges, it obtains its current position through a GPS tracking system and transmits this position to the operator on the ground, as well as the data it is collecting. This navigation system allows a very reduced energy consumption, so the autonomy of the vehicle can be several days, weeks or even months. The autonomy of a Glider is much higher but the average advance speed of 0.4 m/s.

On the other hand, another of the disadvantages associated with these vehicles that are currently being worked on in their recovery of the environment, since this task is the one that usually entails a higher risk of damage. Systems are being developed such as charging stations, where the vehicle can be connected and download the data obtained and recharge the batteries without the need to remove it from the water.

A basic GUS design is showed in Figure 1. Bayesian networks are an excellent alternative for decision trees because they allow the elaboration and representation of more complex models that more faithfully represent an event of reality.

Bayesian networks base their application on non-classical statistics, based on Bayes' theorem, and make inferences when the expert's judgment or a priori knowledge is integrated with the databases, and with this, an inference is made between any subset of variables.

Fig. 1. A GUS basic design. (Virginia Tech Underwater Glider)



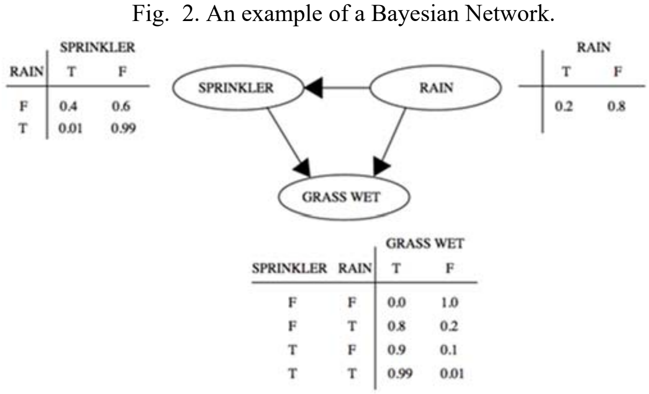
A Bayesian Network is made up of two essential parts:

1. The structure of the model that it is defined as the qualitative part: a graph directed to cyclic (GDC), where each node represents a random variable, and the arcs represent probabilistic dependencies between variables.

A Bayesian network is composed of nodes, which represent variables of any type, although it is more widespread to use discrete variables, where the relationship between them is quantified by a distribution of conditional probabilities that determine the final value of those nodes that have not been loaded as evidence.

The relationship between the variables is defined using arcs that define a causal determination between nodes. See Figure 2.

Fig. 2. An example of a Bayesian Network.



Learning is one of the characteristics that define systems based on artificial intelligence; it can be affirmed that without learning there is no intelligence. It is challenging to define the term learning, but most of the definitions found in the literature agree that it is one of the characteristics of adaptive systems that can improve their behaviour based on their experience, for example when solving similar problems.

The learning in the Bayesian networks consists of defining the probabilistic network from data stored in databases.

This type of learning offers the possibility to define the graphic structure of the network from the observed data or the database and to define the relationships between the nodes also based on said cases; Within the learning of the Bayesian Networks, two phases have been defined:

1. Structural Learning: We must obtain the structure of the Bayesian Network with their particular relations. This type of learning largely depends on the type of network structure, that is, structures such as trees and multi-connected networks.

2. Parametric Learning: It consists of finding parameters associated with a given structure of a Bayesian network; these parameters are formed by the probabilities of the root node and the other variables.

There are different learning algorithms, including:

1. EM (Expansion Maximization): You do not need complete data for learning, and it contains 2 phases: Expansion: calculation of all possible probabilities throughout the network and Maximization: the highest probability is chosen

2. ML (Maximum Likelihood): allow to complete data to be able to learn. It is similar to EM, but without the first phase, that is, without expansion.

2. OUR BBN DESIGN UNDER THE UNDERWATER GLIDER

The development of our BBN in this article follows a five-step process:

1. Describe the aim and context of the BBN.
2. Gather and group information relevant to the context into nodes.
3. Connect the nodes with directional arcs.
4. Determine the conditional probability tables (CPT) and quantify the model.
5. Test and validate the model.

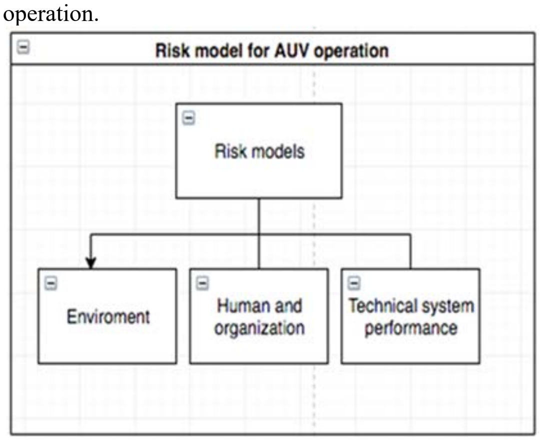
The accompanying sub-areas clarify the advancement procedure in detail. The accompanying sub-areas clarify the advancement procedure in detail.

Step 1 - Define the aim and context of the model

The creation of the model in the article it is essential and to allow to demonstrate the connection between human administrator execution, and the specialised execution of the self-governing framework. The displayed model will help amid the arranging of an AUV mission to recognise potential issues that may emerge. The model in this article can likewise be utilised as a guide amid the structure of a framework since it features vital connections between the human administrators and the specialised framework.

Figure 3 exhibits that a general risk show for AUV task should consolidate points of view related to the particular system, biological conditions, and human and various levelled segments. Rules from the experts, accomplice necessities, and societal wants are furthermore issues that ought to be considered.

Fig. 3. The main aspects to include in an overall risk model for AUV operation.



B. Step 2 - Gather and group relevant information

The human self-governance association gives pertinent data to the model in this article and decides the reason for the improvement of the hubs. Given the meaning of GUS, we may bunch the writing used to form the model into two by and broad classifications:

1. Autonomy and robotization,
2. Human and hierarchical factors in hazard displaying.

C. Step 3 – Connect the nodes

The circular segments in the BBN show are created dependent on the discoveries and the connections recognized between variables. These discoveries were converged, to decide the system. A few elements affect one another. These elements make it hard to characterize these bends unmistakably. Since BBN are non-cyclic, it is absurd to expect to show shared impacts. To determine shared impacts, the most much of the time referenced heading of impact characterize these generally equivocal circular segments.

D. Step 4 - Conditional probability tables and case study

A few different ways of CPT elicitation exist, the most frequently used is watched frequencies or master gauges.

Vinnem et al. use a methodology dependent on structure capacities to evaluate CPTs. This procedure was used in this paper since it lessens the measure of elicitation required. The procedure centres around evaluating the quality of impact from parent hubs on their son's hubs and structure formats. It is accepted that the parent hubs are free. The adjusted strides are:

1. Characterise formats for the CPT evaluation dependent on triangular appropriations;
2. Decide the quality of impact of each parent hub on the tyke hub, and
3. Join the layouts with the separate loads in the CPT of the parent hub.

For sure hubs, the CPT evaluation should be adjusted for the HAC demonstrate. Our BBN model relies upon the self-ruling usefulness structured, and it is inside of the specialized framework, the human administrators, the connection between the specialized framework and the human administrator, and the association in which the administrator's demonstration.

A correct BBN model is related to a high likelihood for a successful mission. Figure 2 demonstrates the BBN model. Human Operator Performance in participation with a self-sufficient framework is broadly examined. It is impacted by Trust, Reaction Time of the administrators, Procedures, Fatigue, Situation Awareness (SA), Workload, Operators' Training, and Operators' Experience.

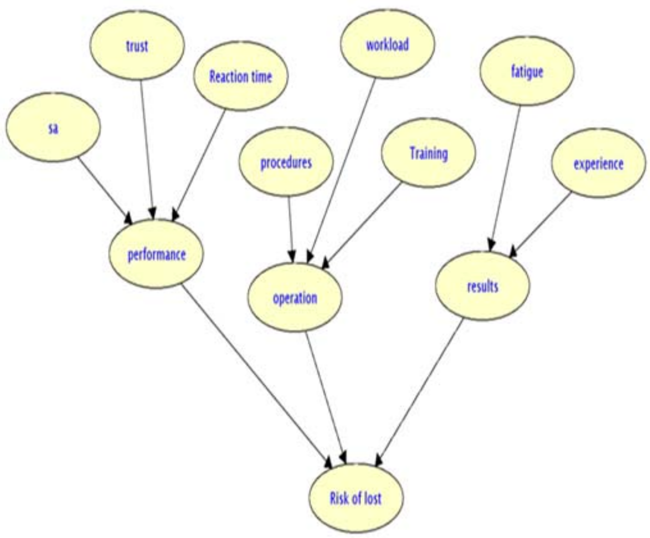
Experience and preparing allude to every single operational part of UV task. However, this allows to incorporates UV programming, UV support, UV sending and recuperation, appraisal of the marine condition, and working in the marine condition.

Research of human self-rule joint effort centers around SA. SA of Human Operators is affected by Trust, Workload, Feedback from the System, Time Delay of Transmission, Communication, and Operators' Training. As can be observed in Figure 4, it can be seen that three great sets intervene in the proposed model.

The three aspects of characterisation are the following:

1. Aspects of performance. It consists of three essential elements, trust, reaction time and SA;
2. Aspects of operation. Allow to formed by the procedures the workload and the training.
3. Aspects of results. It is made up of fatigue which is evaluated in high medium or low and experience which is evaluated in small, medium and large.

Fig. 4. BBN for Human Autonomy Performance (HAP).



Assuming all nine variables are binary, with one representing true and false, the probability tables for the network might be defined as table 1.

Table 1. Characterization of Parameters.

P(SA)	
True	False
0.8	0.2

P(trust)	
True	False
0.05	0.95

P(Reaction Time)	
True	False
0.15	0.85

P(procedure)	
True	False
0.35	0.65

P(workload)	
True	False
0.05	0.95

P(Training)	
True	False
0.6	0.4

P(fatigue)	
True	False
0.8	0.2

P(experience)	
True	False
0.8	0.2

P(performance|SA,Trust,Reaction time)				
SA	TRUST	R.TIME	True	False
F	F	F	0.0	1
F	F	T	0.3	0.7
F	T	F	0.54	0.46
F	T	T	0.6	0.4
T	F	F	0.6	0.4
T	F	T	0.7	0.3
T	T	F	0.8	0.2
T	T	T	1.0	0.0

P(operation|procedure,workload,training)				
procedure	workload	training	True	False
F	F	F	0.0	1.0
F	F	T	0.3	0.7
F	T	F	0.3	0.7
F	T	T	0.7	0.3
T	F	F	0.4	0.6
T	F	T	0.8	0.2
T	T	F	0.7	0.3
T	T	T	1.0	0.0

Fatigue	*experience*	*True*	*False*
F	F	0.0	1.0
F	T	0.4	0.6
T	F	0.4	0.6
T	T	1.0	0.0

P(risk|performance,operation,results)				
procedure	workload	training	True	False
F	F	F	0.0	1.0
F	F	T	0.4	0.6
F	T	F	0.3	0.7
F	T	T	0.65	0.35
T	F	F	0.4	0.6
T	F	T	0.85	0.15
T	T	F	0.65	0.35
T	T	T	1.0	0.0

Once the parameters of the Bayesian network have been defined, they can be used to calculate any conditional probability. Bayesian networks are very convenient to represent systems of causal probabilistic relationships.

For the creation of the proposed Bayesian network, the SamIam modelling software was used. SamIam is a tool for modelling Bayesian networks, developed in Java by Professor Adnan Darwiche and his group for a research paper for UCLA.

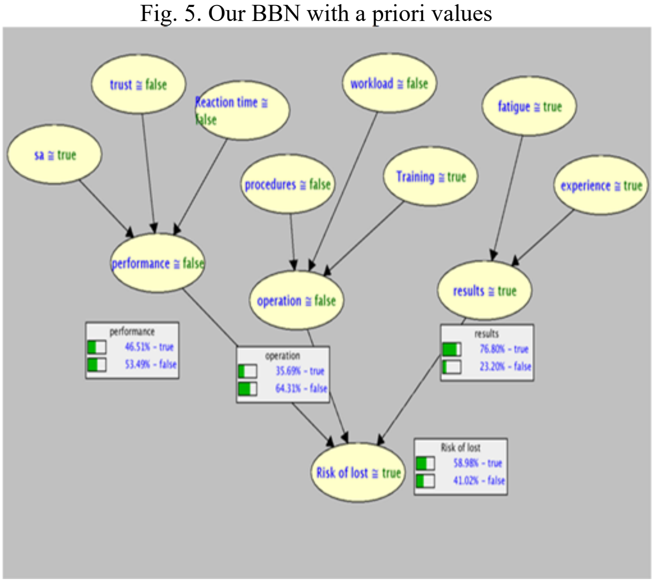
SamIam is composed of two main components:

1. A graphical user interface:
2. A reasoning engine:

The reasoning engine supports many tasks, including classical inference; parameter estimation; space-time compensations; sensitivity analysis; and explanation-generation based on MAP and MPE.

After the characterization of values according to the a priori values shown above, the technical evaluation shows a performance of 46.51%, an operation of 35.69% and evaluation of results in 76.80%. With these values, the risk of loss of the maritime vehicle is 58.98% to maintain it and 41.02 to lose it. Figure 5 shows the evaluated results.

Fig. 5. Our BBN with a priori values



degree of freedom. Any motion perpendicular to the wheel is resisted by contact friction.

Table 2 shows the construction parameters of the BBN.

Table 2. Construction parameters.

Parameter	*Value*
Edges	11
Domain cardinality	largest: 2, smallest: 2, average: 2, median: 2, mode: 2 (x12).
# CPT parameters	largest: 16 parameters, smallest: 2 parameters, average: 6, median: 2, mode: 2 (x8)
Total parameters	72
Nodes	12

With the generated data, a JAVA program was carried out to facilitate the tests carried out. The code developed in the sample in Listing 1.

Listing 1. Main procedure in Java

```
public BeliefNetworkcreateModel()
 {
BeliefNetwork model = new BeliefNetworkImpl();
String[] binary = new String[] { "true", "false" };
model.addVariable( new FiniteVariableImpl( "parent00", binary ), true );
model.addVariable( new FiniteVariableImpl( "parent01", binary ), true );
model.addVariable( new FiniteVariableImpl( "parent02", binary ), true );
model.addVariable( new FiniteVariableImpl( "parent03", binary ), true );
model.addVariable( new FiniteVariableImpl( "parent04", binary ), true );
return model;
 }
```

Validation of the model

The model produces expected outputs regarding the overall model behavior in the case study. Setting the input nodes to their best states resulted in a high probability of 95.1 %. Setting the variable input nodes to the worst case in the case study results in 23.4 %. The presented BBN model is sensitive to the input. The model reflects that the Reliability of Autonomous Functions and the Operators' Experience and Training are very influential.

Discussion

The BBN in this article is explicitly developed for the underwater glider operation and merges the findings from the human autonomy interaction literature. The case study shows that our BBN can produce meaningful results. The sensitivity analysis shows that our model in the case study can be improved most significant in two ways:

1. Through better training and inclusion of experienced operators;
2. Through improved Reliability of Autonomous Functions and SA of vehicles.

However, our BBN is only a sub-model of the overall risk model, but the influence on mission success remains to be modelled, and this could be our next research.

Although the model is sensitive to changes in most of the input nodes, some of them only have a minor influence. These input nodes are related to communications. False Alarm Rate, Interface Design, Mission Duration, Task Load, and Time Delay of Transmission. However, these nodes are associated with Human Operator Performance.

3. CONCLUSION AND FURTHER WORK

This article presents a detailed BBN for human autonomy for a Glide Underwater System (GUS). The case study and development focus on Autonomous Underwater Vehicle (AUV) operation. The BBN can be used for assessment of mission success of GUS operation, during the planning and preparation phases.

The human operator cannot be neglected and is a decisive factor in AUV and GUS operation. Nodes included in this model, which were not mentioned previously in the literature in connection with the operation of AUV and human autonomy interaction, are Human Fatigue, and SA of vehicles.

Our design was similar to Donmez et al., which assess the influence of certain factors on the mission outcome, can aid in validating and improving the model.

Our BBN model is adaptable to other autonomous marine systems or autonomous surface vehicles. They are remotely supervised, and intervention is necessary only in a few cases. Some of the nodes' states might need adaption to the specific cases of these other systems. Necessary adaptions to other systems need to be further investigated in the future.

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