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HUMAN OR ELECTRONIC VESSEL NAVIGATION

This paper explains some strategies for allocating tasks across the human and electronic line of conduct of a vessel . The paper tries to define what should master do, and what should be left to the system. The allocation strategy has to be defined by the nature of the tasks to be performed by the system; the situational milieu in which the system will operate and the power of advanced analytical methods. The Bayesian belief network has been used to quantify the proposed system. Using proposed conditional probabilities the results define that the overload of the master is designed to 30% of the time in the worst case, with normal load during 18.9% of the time.

INTRODUCTION

Today ship managers perform complex tasks. They must be well aware of external situations - accidental threats, for example - as well as of the internal status of all systems, and options for dealing with faulty equipment, in combination with commercial realities and international laws. The ship can be at sea for a long period of time, progressing to its destination port on around the clock basis. The operational environment for the people running ships can be pitching and rolling for days, given certain weather patterns. In fact onboard life is highly demanding and tiring.

General accident statistics for ships have shown little improvement despite the technological advances in ship design. The human element thus remains a critical factor in the maritime safety, and consequently integrative approach of evaluation of the human and technological hardware safety is required.

20 - 90 % of shipboard accidents are stated to have been caused by human error. This is comforting for ship managers as it implies that there is little or nothing that can be done to prevent most accidents. This is not true, because better management can prevent most accident.

Information engineering could provide the means for extending automation by making systems independently capable of diagnostic and predictive decisions, providing a coherent picture of ship environment in uncertain and changing sea states and operational requirements. Special impact of information systems on ship operation has to be focused on ship safety. It has to be stressed that information system does not aim to eliminate operator, but to improve his performance.

The electronic revolution has been an accomplice to a reduction in manning levels so drastic that a medium-sized refer ship which, 25 years ago, might have had a crew of 50 or more, would now sail with less than 20.

The major question exercising the minds of today's ship designers and operators is how best to achieve the goal of one-man bridge and how to find the optimum way of combining into a coherent package a great number of systems and subsystems which, together, comprise a ship. It must be understood that basic elements in any operating system are human operator, the technical system, the man/machine interface and operational procedures.

A system can be fully automated or based on manual operation, but most of them will be a combination of the two. It is important that the technical system and the shipboard personnel can meet equivalent functional requirements and, if necessary, replace each other. These ensure that the system configuration has the same degree of reliability whatever the distribution of manual and automatic performance may be.

This paper tries, using Bayesian network approach, to investigate what are the probabilities that the electronic system could completely supersede the human on board.

THE BAYESIAN APPROACH

A belief network (also known as a Bayesian network or probabilistic causal network) captures believed relations (which may be uncertain, stochastic, or imprecise) between a set of variables, which are relevant to some problem. They might be relevant because we will be able to observe them, because we need to know their value to take some action or report some result, or because they are intermediate or internal variables that help us express the relationships between the rests of the variables.

A Bayesian network is a graphical model for probabilistic relationships among a set of variables. Over the last decade, the Bayesian network has become a popular representation for encoding uncertain expert knowledge in expert systems. Bayesian network is a graphical model for probabilistic relationships among a set of variables.

To understand Bayesian networks and associated learning techniques, it is important to understand the Bayesian approach to probability and statistics. In this section, we provide an introduction to the Bayesian approach for those readers familiar only with the classical view. The Bayesian probability of an event x is a person's degree of belief in that event. Whereas a classical probability is a physical property of the world (e.g., the probability that a coin will land heads), a Bayesian probability is a property of the person who assigns the probability. One common criticism of the Bayesian definition of probability is that probabilities seem arbitrary. With regards to the first question, many researchers have suggested different sets of belief. Properties that should be satisfied by degrees of belief It turns out that each set of properties leads to the same rules: the rules of probability. Although each set of properties is in itself compelling, the fact that different sets all lead to the rules of probability provides a particularly strong argument for using probability to measure beliefs. In general, the process of measuring a degree of belief is commonly referred to as a probability assessment. The technique for assessment that we have just described is one of many available techniques discussed in the Management Science, Operations Research, and Psychology literature. Nonetheless, in most cases, probabilities are used to make decisions, and these decisions are not sensitive to small variations in probabilities.

A Bayesian belief network is used to model a domain containing uncertainty in some manner. Elsewhere, the shorter terms belief network and Bayesian network are used and also in the past, the term causal probabilistic networks have been used. A Bayesian belief network is a directed acyclic graph where each node represents a random variable. Each node has the states of the random variable it represents and a conditional probability table or in more general terms a conditional probability function. The conditional probability table of a node contains probabilities of the node being in a specific state given the states of its parents.

Bayesian belief networks are often used to model domains that are characterized by inherent uncertainty. (This uncertainty can be due to imperfect understanding of the domain, incomplete knowledge of the state of the domain at the time where a given task is to be performed, randomness in the mechanisms governing the behaviour of the domain, or a combination of these.)

Formally, a Bayesian belief network can be defined as follows:

A Bayesian belief network is a directed acyclic graph with the following properties:

- Each node represents a random variable.

- Each node representing a variable S_i with parent nodes representing variables $S_{\pi(1)}, S_{\pi(2)}, \ldots, S_{\pi(n)}$ is assigned a conditional probability table).

The nodes represent random variables, and the edges represent probabilistic dependences between variables. These dependences are quantified through a set of conditional probability tables. Each variable is assigned a conditional probability table of the variable given its parents. For variables without parents, this is an unconditional (also called a marginal) distribution.

Bayesian network (also known as directed graphical model) is specified numerically by associating local conditional probabilities with each of the nodes in an acyclic directed graph. These conditional probabilities specify the probability of node S_i given the values of its parents, i.e., $P(S_i|S_{\pi(i)})$, where $\pi(i)$ represents the set of indices of the parents of node S_i and $S_{\pi(i)}$ represents the corresponding set of parent nodes To obtain the joint probability distribution for all of the N nodes in the graph, i.e., $P(S) = P(S_1, S_2, \ldots, S_N)$, we take the product over the local node probabilities:

$$P(S) = \prod_{i=1}^{n} P(S_i | S_{\pi(i)}) \qquad (1)$$

Inference involves the calculation of conditional probabilities under this joint distribution. The problem of probabilistic inference in graphical models is the problem of computing a conditional probability distribution over the values of some of the nodes (the "hidden" or "unobserved" nodes), given the values of other nodes (the "evidence" or "observed" nodes). Thus, letting H represent the set of hidden nodes and letting E represent the set of evidence nodes, we wish to calculate $P(H|E)$:

$$P(H|E) = \frac{P(H,E)}{P(E)} \qquad (2)$$

General exact inference algorithms have been developed to perform this calculation (Jensen, 1996; Shachter, Andersen, & Szolovits, 1994; Shenoy, 1992). These algorithms take systematic advantage of the conditional independencies present in the joint distribution as inferred from the pattern of missing edges in the graph.

THE MODEL

One way to categorize problems locates them within multidimensional spaces such as the Herman's situation cube.

This three dimensional space locates problems along three dimensions: threat, decision time and awareness. Eight different situations are recognized:

Table 1. Situations from Herman's situation cube

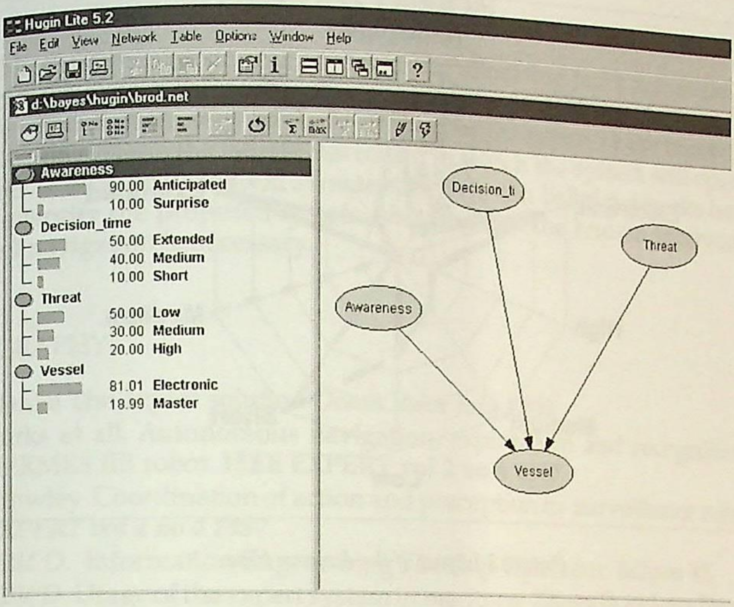
A	Crisis	High threat	Short decision time	Surprise
B	Innovative	High threat	Extended decision time	Surprise
C	Inertial	Low threat	Extended decision time	Surprise
D	Circumstantial	Low threat	Short decision time	Surprise
E	Reflexive	High threat	Short decision time	Anticipated
F	Deliberative	High threat	Extended decision time	Anticipated
G	Mutinied	Low threat	Extended decision time	Anticipated
H	Administrative	Low threat	Short decision time	Anticipated

Mostly all the situations on board are mutinied, and although it seems that there is always sufficient time, there are the situations where a person on board has to operate in crisis real-time conditions. The Bayesian model using Herman's dimensions – threat, decision time and awareness has been introduced using computer program Hugin Lite from Hugin Expert co. Denmark. The initial probabilities could be seen from the Picture 1, representing the screen view of the program.

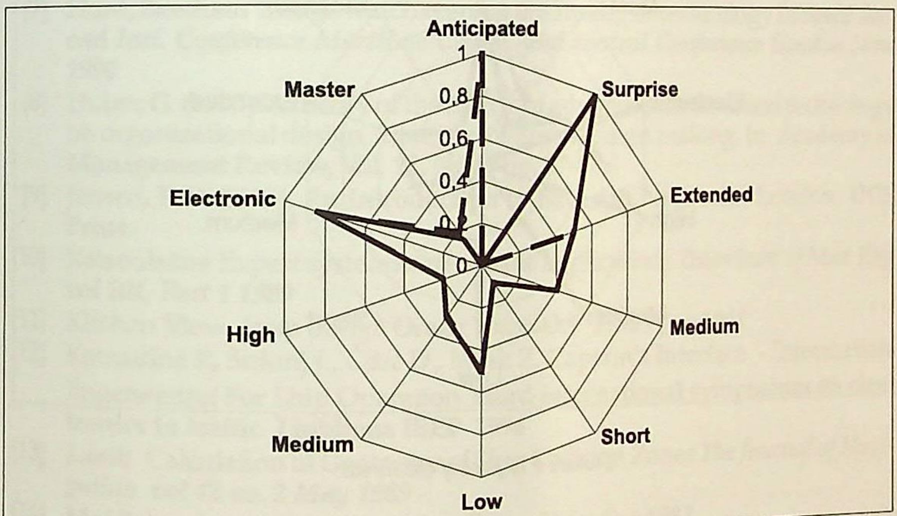
THE RESULTS

Initial results, based on presumed probabilities show that the electronic system could be used on the vessel for 81.01 % of the time, and for 18.99 % of the time human surveillance and supervision is necessary.

The maximal normal propagation method can be used in Bayesian belief networks containing only discrete chance nodes to find states belonging to the most probable configuration. If a state of a node belongs to the most probable configuration it is given the value 100. All other states are given the relative value of the probability of the most probable configuration they are found in compared to the most probable configuration. Using this method the results show that the electronic system could steer the vessel maximally in 100% of the time, and the human intervention is needed in maximally in the 30% of the time.

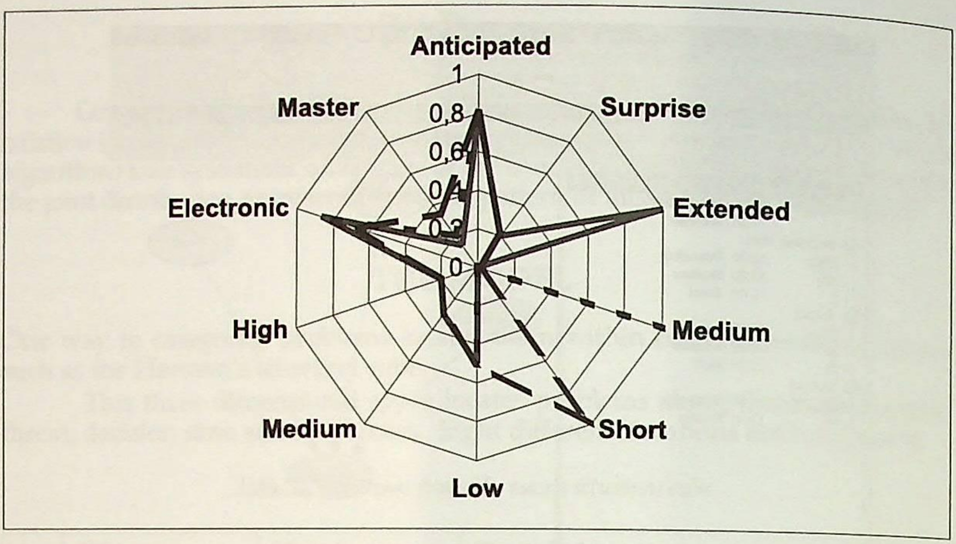


Picture1 The Computer model

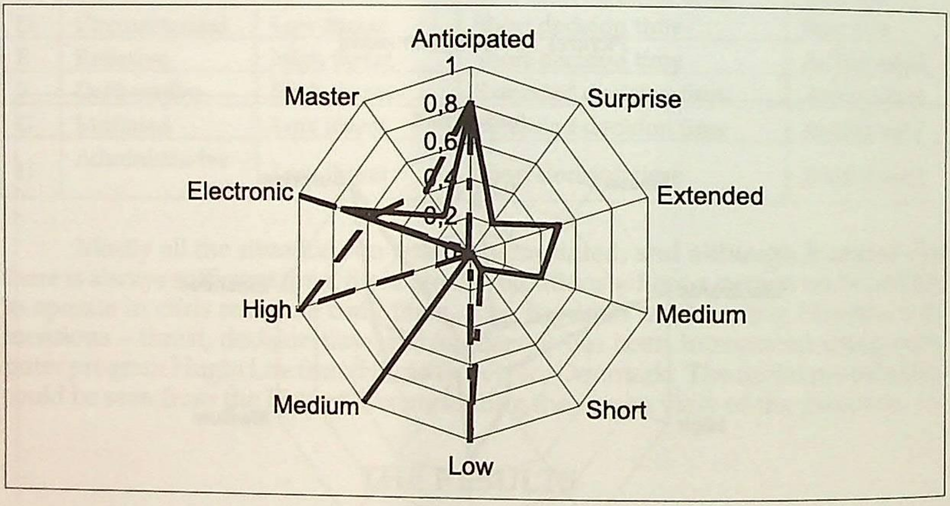


Picture 2 Impact of the awareness

The impact of the awareness is shown at Picture 2, and the difference in the results arising from the probabilities variation from 100 % to 0% for anticipated awareness (resulting in 0% and 100% for surprise) shows the 84.7% and 80.6 % of sail time usable for the electronic system.



Picture 3 Impact of the decision time.



Picture 4 Impact of the threat

The impact of the decision time shown on Picture 3, shows significant increase of the human operation when changing the decision time from extended to short. The probability for the master operation is 14% for the extended time, 20.4% for the medium and 34% for the short decision time.

The impact of the threat shown on Picture 4 shows that the human intervention is needed from 2% for low threat, 24.6 % for medium threat up to 42.2% for high threat.

CONCLUSION

This paper explains some strategies for allocating tasks across the human and electronic components of a vessel computer system using Herman situation cube. The allocation strategy has to be defined by the nature of the tasks to be performed by the system; the situational milieu in which the system will operate and the power of advanced analytical methods. Bayesian belief networks have been used to quantify the proposed system, showing that the human intervention on the vessel navigation is necessary.

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Sažetak

LJUDSKO ILI ELEKTRONIČKO UPRAVLJANJE BRODOM

U radu se nastoje razjasniti neke strategije pri određivanju postupaka upravljanja brodom ljudskim ili elektroničkim putem. Određuje se postupak koji bi trebao izvoditi zapovjednik, te oni koji bi se trebali izvoditi računalom. Taj se strateški postupak treba definirati na osnovi prirode posla definiranog sustavom u zadanoj situaciji uporabom naprednih analitičkih metoda. Za kvantificiranje predloženog sustava korištena je Bayesova mreža vjerovanja. Korištenjem predloženih uvjetnih vjerojatnosti, rezultati pokazuju da zapovjednik mora u 18,9% odnosno, u najgorem slučaju, u 30% slučajeva upravljati brodom.