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IMPLEMENTATION OF NAVIGATORS' KNOWLEDGE IN AN EXPERT SYSTEM FOR THE EVALUATION OF SAFETY OF A SHIP NAVIGATING IN A RESTRICTED AREA

ABSTRACT This article presents possible applications and a methodology of creating an expert system for the evaluation of sailing ship safety in a restricted area that may be utilized by vessel traffic service (VTS) centres. Problems of acquisition of navigators' knowledge relating to the evaluation of moving ship safety are discussed. The knowledge acquired has been implemented in an expert system with the NEXPERT OBJECT program – a tool of the shell type for building expert systems. Possible applications of this type of systems in VTS centres are indicated.

INTRODUCTION

Implementation of the latest technological solutions in marine navigation has been continually enhancing navigational safety standards. More and more importance is put on wider use of the knowledge of expert-navigators through relevant methods and artificial intelligence tools. Measures are taken to support planning, supervision and handling of a vessel by means of systems using knowledge bases. An alternative tool for that purpose are expert systems, built from scratch or based on the so-called expert system shells [Grabowski, 1990]. The determination of their operating range (generally a narrow one) as well as the acquisition and representation of navigators' knowledge for such systems are basic problems to be solved. It is obvious that such systems should operate correctly, be universal, capable of self-analysis and updating their knowledge base [Mulawka, 1996]. In addition to expert systems, other systems may be used for the purpose: artificial neural networks, fuzzy systems, or, in search for optimal solutions, genetic algorithms might be useful. Vessel traffic service centres (VTS or their extended version – VTMS) are a major area of application of this type of expert systems. The operational objective of the expert system in this context is to support decisions made by VTS operators.

FUNCTIONS AND TASKS OF ADVISORY DECISION-AIDING SYSTEMS IN VTS CENTRES

VTS SYSTEM TASKS

Vessel traffic service systems play a vital role in enhancing the safety of navigation in congested areas. The systems are capable of monitoring vessel traffic, which allows their operators to execute their principal tasks [Guidelines]: control of vessel traffic, supervision of navigational services and co-ordination of rescue operations.

The systems enable, inter alia:

- display in an electronic chart or raw video mode,
- track processing,
- communications with a radar subsystem,
- operator control of radar devices,
- recording of radar video, radar tracks, status and other data,
- interchange of data with an external database system.

Principal tasks of VTS operators include tracking and evaluating the current navigational situation, advising vessels on dangers to the vessel traffic. This function is performed by warning alarms activated when, e.g. a vessel enters a prohibited area or deviates from its designated traffic lane. Multitudes of situations impose difficulties in accounting for all-important factors. The are no tools enabling an uptodate automatic evaluation of the situation in view of detecting potential threats and avoiding accidents.

An expert system may provide vital assistance in supporting decisions taken by VTS operators. Such a system would feature a function of port regulations observance control, algorithms of vessel motion optimization which solve problems of conflict situations and tools for evaluating navigational safety in a fairway.

APPLICATIONS OF EXPERT SYSTEMS IN VTS SYSTEMS

Possible expert system applications in the systems of vessel traffic service result directly from the functions and tasks of the latter and include:

- supervision of compliance with traffic regulations in the area,
- optimization of vessel traffic in the area,
- current analysis and evaluation of the navigational safety,
- identification of dangerous situations,
- decision support in emergency situations,
- co-ordination of actions to be taken in emergency situations,
- collision avoidance.

The choice of expert systems for monitoring regulations observance in a given area is justified - such regulations and rules are quite complex and change in time (as the vessel proceeds). In this case constructing a knowledge base consists in transforming rules contained in traffic regulations into a form suitable for an expert system metalanguage.

The optimization of vessel traffic is dictated by safety reasons as well as economic factors, connected with the costs of vessel berthing and services in a port. The determination of an optimal ship motion schedule in a specific area accounting for limitations caused by other ships may be treated as a control theory problem: determine $v_i(t)$, whilst the limitations are satisfied, so that the times of waiting for port entry and passage through a given area are minimized. As a rule, limitations taken into account are those resulting from the regulations in force and the availability of facilities needed to execute a transportation task (free berth, tugs etc.) [Furstenberg, 2000]. Simple models of vessel movement prediction are usually used to solve the problem.

Most VTMS systems are capable of generating warning alarms when pre-defined dangerous situations occur, e.g. entering an area closed for navigation. However, these systems do not analyze or evaluate the current situation; they do not detect potentially dangerous situations in advance. These functions are a responsibility of VTS operators.

Emergency procedures are understood as algorithmized procedures to be followed in specific emergency situations. One example of this is an expert system incorporating procedures for dangerous goods carriage. The expert system in this case has to identify a threat and generate procedures to be followed in a given situation. An extended version of such a system is a decision support system, which enables a choice of procedures accounting for, assumed criteria and their priorities.

The problem of collision avoidance, namely collision avoiding manoeuvres, may be difficult because in restricted areas a range of possible manoeuvres is often limited. If a dangerous situation is detected too late, a collision will be imminent, but actions may be taken to minimize the effects. Consequently, the analysis and evaluation of a navigational situation play a key role. The current change trend provides a basis for the identification of dangerous situations. This function may be performed by an expert system. VTS systems have an open architecture so the application of typical data transmission interfaces makes it possible to incorporate software operating in the expert system technology. Such programs enable effective evaluation of a fairway traffic situation and support of decisions on vessel traffic accounting for detailed rules of the regulations in force.

AN EXPERT SYSTEM FOR NAVIGATIONAL SITUATION EVALUATION

EVALUATION OF A NAVIGATIONAL SITUATION

The evaluation of navigational safety or risk is vital for VTS operators taking crucial decisions concerning vessel traffic. In most vessels systems the accepted criteria used are the closest point of approach (CPA) and the time to closest point of approach (TCPA). A situation is identified as a collision situation when the closest point of approach (CPA) is not maintained. These criteria, however, are difficult to apply in restricted areas, particularly in narrow channels or fairways.

In assessing a traffic situation in a restricted water area the information on factors affecting the navigational safety of a ship is crucial. From the criteria resulting from the regulations in force in a given area and his own knowledge the VTS operator evaluates a situation. Basic parameters affecting the evaluation by a VTS operator are, in addition to ship and area dimensions, ship's position and current course, speed and rate of turn, distance to a danger and external factors such as wind force and direction, current direction and speed.

ASSUMPTIONS FOR AN EXPERT SYSTEM

The task for the type of expert system in question may be formulated as a typical task of a diagnostic system: evaluation of the existing (navigational) situation, based on the available data. The system should have an essential property of being capable of explaining generated conclusions on the navigational safety. In [Pietrzykowski, 1997] the evaluation of navigational situations is presented, in which artificial neural networks with fuzzy logic are used. With specific navigational situations assessments done by experienced navigators, the process of network learning was performed. The network responses for specified input parameters made up a quantitative measure of navigational safety level. However, this method of non-symbolic representation of knowledge does not allow interpreting the navigational situation in the form of rules readable for the VTS operator who has to interpret the situation himself. It is vital to obtain evaluation criteria as clear as possible for the decision support system to be reliable. In this case criteria based on rules or decision trees are much more readable, as they enable classifying a situation. The adoption of an expert system based on rules necessitates a classification of situations and the specification of classification methods. The classification task for a specific ship i has the following form:

$$K = f(p_i, p_a, p_z, p_r) \qquad (1)$$

where: *i* – identifier of a vessel on the fairway

p_i - vessel i parameters,

p_a - area parameters,

p_z - parameters describing external conditions (visibility, wind, current).

p_r - parameters describing other traffic situation, The following classification of a navigational situation has been assumed:

- 2 classes: safe situation – dangerous situation
- 3 classes: safe situation – intermediate situation – dangerous situation.

This type of classification is a natural one as used by the human-operator. Since untypical, unrecorded situations not found in the knowledge base might occur, it seems purposeful to supplement the classification to include unidentifiable or non-interpretable ones if the system is to operate correctly and reliably.

ACQUISITION AND REPRESENTATION OF THE KNOWLEDGE OF EXPERT NAVIGATORS

The acquisition and representation of navigators' knowledge for the evaluation of navigational situations is a complex problem. Apart from taking into account formal local and international regulations, such as the International Regulations for the prevention of Collisions at Sea, often general enough to be interpreted differently, navigators use their own experience. The experience is difficult to be translated into unequivocal rules or decision trees. That is why attempts are aimed at automatic knowledge acquisition. Principal methods of acquiring rules include interviews with experts, mathematical models and machine learning, which consists in obtaining rules from examples. The latter requires gathering data containing decisions of experts and conditions that affected a specific decision. Then certain methods are used to identify regularities in a data set and to generate decision rules identical with the decisions made by an expert. There are various methods and tools for data exploration: statistics, fuzzy set theory, approximated sets theory, analysis of concentrations, artificial neural networks or genetic algorithms.

In [Pietrzykowski, 2000] a method was proposed for acquiring knowledge and decision rules from expert studies based on simulated research utilizing algorithms of machine learning: FOIL and C4.5 [Quinlan, 1990, 1993].

Both systems take a data set as input and develop a symbolic "theory" to explain the data. The data set consists of examples, where one "example" is a snapshot of a ship at a particular point in time (position, heading, etc.), plus a classification (e.g., safe/dangerous). A "theory" explains the data if it can reproduce the classifications. Theories are normally developed and tested by taking the available data, partitioning it randomly into two sets, "learning" a theory with one set, and testing the theory with the other set.

C4.5 is a learning algorithm that generates decision-trees from a set of data. Conceptually, all data begin at the root of the tree. The data are split according to some criterion into subsets; for example, if the criterion were "course heading 5 degrees" then examples with values less than this would be in one group, and examples with values greater than this would be in the second. The subsets are then split according to a second criterion, and the process continues with the goal of creating groups that are all of the same class (for example: dangerous/safe).

The second algorithm, FOIL, works very differently, producing a series of logical rules like one might encounter in an expert system. The goal is the same: to separate the data according to their evaluation as dangerous or safe. The rules can be written from either viewpoint, dangerous or safe, and define the criteria that must be met for the classification to be correct. For example, one rule for "dangerous" might require the ship to be within 10 meters of the shore. The system begins with an empty rule-set, and develops rules one after the other until it has covered as many examples in the data as possible.

While both algorithms try to perfectly partition the data according to the classification, this may not be completely achievable. First, the data may be internally inconsistent – this is often the case when the classifications in the data are subjective, as is the case here. Second, it may not be desirable, as there is a danger of "overspecialization", and learning algorithms are designed to avoid this even if it means an imperfect classification.

Overspecialization happens when data are sparse. Suppose that a learning system has come to the point where the theory "almost" explains the data. Any further changes will accommodate single examples. Since examples may differ on many attributes, there is no way for the system to be certain which attribute is relevant, since it is working with single examples. Which means that there is a real danger that the system will pick the wrong attribute, and create a theory that works for the training data, but is actually erroneous.

RESEARCH

EXPERT RESEARCH

The values of navigational safety were acquired in simulated passages in a restricted area by expert research methods. The assumed assessment was a real value from the <0, 1> interval, where the value 0 means a safe situation, while '1' means a dangerous situation. Simulated ship passages were performed on a Ship Handling Simulator NMS-90.

A model of a bulk carrier 95.5-m in length, 18.2-m beam and 5m draft was used in the research. The vessel proceeded at 8 knots. The area comprised a straight stretch of a fairway 200 meters wide. Participants had various shipboard experiences: captains, 3rd class deck officers as well as navigators with short sea service. They assessed (real value from the <0, 1> interval) navigational situations at 15 second intervals. During the simulated passages certain values were recorded automatically, e.g. deviation from the recommended course, deviation from the fairway axis, ship's rate of turn.

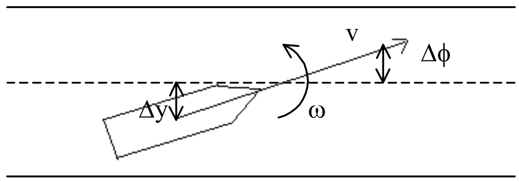

Fig. 1. A navigational situation on the fairway:
v – ship's speed,
Δy - shift from the fairway axis,
Δϕ-deviation from the recommended course,
ω- ship's angular speed.

The positive values were assumed to denote a shift to starboard from the fairway centre line (axis), deviation from the recommended course to starboard and ship's rate of turn to starboard relative to the ship's centre line while negative values denote respective changes to the port side.

From the recorded data and evaluations of particular situations performed by experts an attempt was made to develop readable criteria of evaluation in the form of rules and decision trees.

KNOWLEDGE ACQUISITION

The research aimed at defining evaluation criteria from the facts gathered during an experiment. The criteria are supposed to identify a navigational situation as one of the two or three categories: safe – dangerous and: safe – intermediate - dangerous. For the evaluations to be objective mean values of evaluations of particular situations were taken into account. These mean values were determined from the evaluations of individual experts (a group of 6 navigators – master mariners) 300 facts were recorded in total. The acquisition of rules and decision trees was executed for 85 % of the facts, with the 15% randomly chosen facts left for verification.

The following form of a classification task K with n classes ($K=\{k_1,..., k_n\}$) was adopted:

$$K= f(p_i, \Delta y_i, \Delta\phi_i, \omega_i) \quad (2)$$

where: *i* – ship's identifier on the fairway
p_i – ship's i parameters,
Δy_i – ship's i deviation from the fairway centre line [m],
$\Delta\phi_i$ – ship's i deviation from the preset course [°],
ω_i – ship' i rate of turn [°/min.].

The classification was performed for the situation categories specified in section 3.2.

FOIL

This algorithm allows generating logical rules for the task of classifying data into two classes (areas). The generated rules describe criteria for assigning data to a given class; data, which do not meet those criteria, belong to the other class. The algorithm, from the set of relations classified into the selected class k_j:

$$(p_i, \Delta y_i, \Delta\phi_i, \omega_i) \tag{3}$$

produces the rules in the form of Horn clause definitions. For the ship i described by parameters p_i the rules are as follow:

$$k_j(\Delta y_i, \Delta\phi_i, \omega_i)\text{: if constraint}_{\Delta y}(\Delta y_i)\text{ and constraint}_{\Delta\phi}(\Delta\phi_i)\text{ and constraint}_{\omega}(\omega_i) \quad (4)$$

where constraint$_{\Delta y}$, constraint$_{\Delta(}$and constraint$_{(}$describe, respectively, constraints for the current variables Δy_i, $\Delta\phi_i$, $\omega_{i.}$

This method excludes separating a larger number of classes at one time, e.g. a class of intermediate situations. Therefore, the following partition has been assumed:

1) class I: facts for the evaluation of a navigational situation in the <0, 0.5> range – safe situation
2) class II: facts for the evaluation of a navigational situation in the <0.5, 1> range – dangerous situation.

Figures 2 and 3 present rules for classes i and II.

Safe_situation(dy,dfi,omega) : If dy<=27.69 and >-16.83 and omega>-8.9.
Safe_situation(dy,dfi,omega) : If dy<=27.69 and dfi<=7.9and omega<=-9.2.
Safe_situation(dy,dfi,omega) : If dy>-32.04 and dy<=11.4 and dfi>-2.4.
Safe_situation(dy,dfi,omega) : If dfi<=-2.5 and dfi>-10.2 and dy<=34.21 and dy>-25.52.
Safe_situation(dy,dfi,omega) : If dy>-39.64 and dfi>4 and omega>-17.1 and dy<=20.09.
Safe_situation(dy,dfi,omega) : If dy>-32.04 and dy<=29.86 and dfi<=-3.1 and dfi>-7.
Safe_situation(dy,dfi,omega) : If dy<=29.86 and dy>23.35 and omega>-9.7.
Safe_situation(dy,dfi,omega) : If dy>35.29 and dy<=36.38 and omega>-14.9.
Safe_situation(dy,dfi,omega) : If dfi<=0.5 and omega<=-25.5.
Safe_situation(dy,dfi,omega) : If omega<=-13.4 and omega>-17.1 and dy<=28.78.
Safe_situation(dy,dfi,omega) : If dfi<=-3.8 and dfi>-4.6 and dy<=37.47.
Safe_situation(dy,dfi,omega) : If dfi<=-8.2 and dfi>-11.8 and dy>-24.43.
Safe_situation(dy,dfi,omega) : If omega<=-20.1 and omega>-21.7.
Safe_situation(dy,dfi,omega) : If dfi>2.3 and dfi<=2.4 and dy>-37.47.
Safe_situation(dy,dfi,omega) : If dfi<=-8.2 and dfi>-10.2.
Safe_situation(dy,dfi,omega) : If dfi>4 and dfi<=4.1.

Fig. 2. Rules for the evaluation of a navigational situation for the classification of situations as: 0 – safe; 1 – dangerous; class I; dy - deviation from the fairway centre line [m], dfi – deviation from the recommended course [°], omega- ship‘s rate of turn [°/Min.].

Dangerous_situation(dy,dfi,omega) : If dy<=-32.04 and dfi<=2.1.
Dangerous_situation(dy,dfi,omega) : If dy>29.86 and dfi<=5.8 and dfi>-1.4.
Dangerous_situation(dy,dfi,omega) : If dy<=-41.81.
Dangerous_situation(dy,dfi,omega) : If dy>34.21 and omega>-9.6 and dfi<=-1.4.
Dangerous_situation(dy,dfi,omega) : If dy<=-22.26 and dfi<=-7 and omega>5.4.
Dangerous_situation(dy,dfi,omega) : If dy>22.26 and dy<=23.35.
Dangerous_situation(dy,dfi,omega) : If dy>27.69 and dfi>-2.5 and omega<=-4.4 and omega>-15.7.
Dangerous_situation(dy,dfi,omega) : If dfi<=3.8 and dy<=-34.21 and omega>2.8.
Dangerous_situation(dy,dfi,omega) : If dfi<=-2.4 and dy<=-16.83 and dfi>-3.1.
Dangerous_situation(dy,dfi,omega) : If dfi<=-6.4 and dfi>-7.1 and omega>-15.1.
Dangerous_situation(dy,dfi,omega) : If dfi<=-15 and dy<=-16.83.
Dangerous_situation(dy,dfi,omega) : If omega<=-17.7 and dfi>0.3 and dy>-38.55.
Dangerous_situation(dy,dfi,omega) : If dfi<=-22.2.

Fig 3. Rules for the evaluation of a navigational situation for the classification of situations as: 0 – safe; 1 – dangerous; class II; dy - deviation from the fairway centre line [m], dfi – deviation from the recommended course [°], omega - ship's rate of turn [°/Min.].

For instance, the first rule of the identification of a dangerous situation (Fig. 3) may be interpreted as follows:

a situation is dangerous – the generated value is "1"-, if the deviation from the fairway centre line Δy to port side is larger than 32.04 [m] and the deviation from the recommended course to starboard $\Delta\phi$ is smaller than 2.1 [°].

The generated rules determine subsets of the domain of the classification function, satisfying the constraints for a selected situation class: safe situation (Fig. 2); dangerous situation (Fig.3).

The generated rules enable a readable evaluation of a navigational situation. It should be noted, however, that the operation of the algorithm has resulted in the generation of rules for individual facts. This may lead to an increased complexity of the rule base of the expert system through a creation of a large number of rules for individual facts.

C4.5.

This algorithm is capable of generating decision trees for solving the problem of classification into two classes or more. In this connection, apart from the same classification as for the FOIL algorithm, another division was introduced with the following classes:

1) class I: facts for the evaluation of a navigational situation in the range <0, 0.4) – safe situation,
2) class II: facts for the evaluation of a navigational situation in the range <0.4, 0.6) – intermediate situation,
3) class III: facts for the evaluation of a navigational situation in the range <0.6, 1> – dangerous situation.

The division of the facts into three classes was done in order to distinguish intermediate situations, which are rather difficult to be assigned to any of the remaining groups. In this way possible errors in the classification are excluded.

The algorithm produces the decision tree from the set of relations (5) for all the defined classes k_j ($K=\{k_1,..., k_n\}$; $j=1..n$)

$$(p_i, \Delta y_i, \Delta\phi_i, \omega_i, k_j) \tag{5}$$

Figures 4 and 5 show generated decision trees for the two classifications.

```
dy <= -32.04 :
|  dfi <= 2.2 : 1 (35.0/1.4)
|  dfi > 2.2 :
|  |  dy <= -41.81 : 1 (9.0/1.3)
|  |  dy > -41.81 :
|  |  |  dfi <= 3.8 : 1 (4.0/2.2)
|  |  |  dfi > 3.8 : 0 (8.0/1.3)
dy > -32.04 :
|  dy <= 29.86 : 0 (164.0/18.3)
|  dy > 29.86 :
|  |  dfi > -2.4 : 1 (19.0/3.7)
|  |  dfi <= -2.4 :
|  |  |  dy <= 34.21 : 0 (6.0/1.2)
|  |  |  dy > 34.21 :
|  |  |  |  omega <= -7.8 : 0 (4.0/2.2)
|  |  |  |  omega > -7.8 : 1 (6.0/1.2)
```

Fig. 4. A decision tree of a navigational situation evaluation for the two-class division of situations: 0 – safe; 1 – dangerous; dy - deviation from the fairway centre line [m], dfi – deviation from the recommended course [°], omega - ship‘s rate of turn [°/Min.].

The first rule for identifying a dangreous situation (Fig. 4) may be interpreted as follows: a situation is dangerous– the generated value is “1”-, if the deviation from the fairway centre line Δy to port is larger than 32.04 [m] and the deviation from the recommended course to starboard $\Delta\phi$is smaler than 2.2 [°].

The generated decision trees determine subsets of the domain of the classification function; the subsets satisfy the criterion for the assumed classes of a navigational situation: safe situation – dangerous situation (Fig. 4); safe situation – intermediate situation – dangerous situation (Fig. 5);

```
dy <= -32.04 :
|  dfi <= 2.2 :
|  |  dy <= -41.81 : 1 (15.0/1.3)
|  |  dy > -41.81 :
|  |  |  dfi > 0.9 : 0.5 (3.0/1.1)
|  |  |  dfi <= 0.9 :
|  |  |  |  dy <= -34.21 : 1 (12.0/2.5)
|  |  |  |  dy > -34.21 :
|  |  |  |  |  omega <= 12.6 : 0.5 (3.0/1.1)
|  |  |  |  |  omega > 12.6 : 1 (2.0/1.0)
|  dfi > 2.2 :
|  |  dy <= -50.5 : 1 (2.0/1.0)
|  |  dy > -50.5 : 0.5 (19.0/1.3)
dy > -32.04 :
|  dy <= 28.78 :
|  |  dy <= 13.57 :
|  |  |  dfi <= -1.3 :
|  |  |  |  dy <= -14.66 : 0.5 (23.0/4.9)
|  |  |  |  dy > -14.66 :
|  |  |  |  |  dfi > -10.9 : 0 (17.0/1.3)
|  |  |  |  |  dfi <= -10.9 :
|  |  |  |  |  |  dy <= 1.63 : 0.5 (7.0/1.3)
|  |  |  |  |  |  dy > 1.63 : 0 (6.0/2.3)
|  |  |  dfi > -1.3 :
|  |  |  |  dy <= 8.14 :
|  |  |  |  |  dy <= -30.95 : 0.5 (3.0/2.1)
|  |  |  |  |  dy > -30.95 : 0 (59.0/3.8)
|  |  |  |  dy > 8.14 :
|  |  |  |  |  omega <= -10 : 0 (3.0/1.1)
|  |  |  |  |  omega > -10 : 0.5 (5.0/2.3)
|  |  dy > 13.57 :
|  |  |  dfi <= 0 : 0 (18.0/8.0)
|  |  |  dfi > 0 : 0.5 (16.0/2.5)
|  dy > 28.78 :
|  |  omega > -5 : 0.5 (11.0/3.6)
|  |  omega <= -5 :
|  |  |  dfi <= -3.1 : 0.5 (10.0/1.3)
|  |  |  dfi > -3.1 :
|  |  |  |  omega > -11.2 : 1 (6.0/2.3)
|  |  |  |  omega <= -11.2 :
|  |  |  |  |  dy <= 37.47 : 0.5 (11.0/2.5)
|  |  |  |  |  dy > 37.47 : 1 (4.0/2.2)
```

Fig. 5. A decision tree of a navigational situation evaluation for the 3-class division of situations: 0 – safe; 0.5 - intermediate; 1 – dangerous; dy - deviation from the fairway centre line [m], dfi – deviation from the recommended course [°], omega - ship's rate of turn [°/Min.].

The class of intermediate situations enables finding the trend of situations changes.

The generated logical rules and decision trees implemented in the expert system enable automatic evaluation of a navigational situation and its explanation.

IMPLEMENTATION

THE SYSTEM EXPERT SHELL

One of the tools known as expert system shells is the program NEXPERT OBJECT [Program, 1994]. The program has extended tools for introducing and edition of rules (knowledge base construction), mechanisms for interference backward and forwards a graphic interpreter of inference processing. The programming language is object – oriented.

The basic elements of its system are objects, classes and methods.

Object – a basic information unit in the system. It may represent any concept of the knowledge base. An object may be an element of a larger set (subclass, class), and it may be assigned some properties.

Class – enables grouping objects with the same basic properties. An object may belong to several classes.

Subclass – an element of a class. a group of objects sharing properties of the superior class.

Property – a feature used for describing objects and classes. Properties are assigned one of the six pre-defined types.

Methods – procedures describing operations on objects.

The relationship between objects is written in the form of rules. The general form of the rule is as follows:

IF LHS THEN hypothesis RHS

where: LHS – (Left Hand Size) any number of conjunctions of logical expressions,
hypothesis – name of a variable assuming only logical values,
RHS – (Right Hand Size) assumes the form:

THEN action_1 ELSE action_2

Action_1 is performed when LHS = True.

Action_2 is performed in the contrary case.

The program NEXPERT OBJECT made it possible to create an expert system prototype in which the generated logical rules and decision tree were implemented.

For instance, a rule generated by the C4.5 algorithm and implemented in the knowledge base of the NEXPERT OBJECT program has the following form:

RULE: R_10
LHS: |data|.dy <= 34.21
|data|.dy > 29.86
|data|.dy > -32.04
|data|.dfi <= -2.4
RHS: ASSIGN 0 |data|.wsp_obl
HYPO: H_10

Satisfying the conditions of the rule (LHS) will attribute the value “0” to the property *wsp_obl* of the class *data* while the hypothesis H_10 will be attributed the value “true”.

The results of a navigational situation identification

Both FOIL and C4.5 algorithms were used to verify the identification and evaluation of a navigational situation of the expert system with knowledge bases created with the use of the two algorithms.

The algorithms FOIL and C4.5, on the basis of facts (navigational situation evaluated by experts) were used to obtain the relationship in a form of simple rules. Then, the rules were implemented as a knowledge base of the expert system by means of the expert shell system, the program NEXPERT OBJECT. The acquired knowledge base was used for a verification of navigational situation evaluation for the source data.

FOIL

The situations were considered as classified correctly when they were assigned only to one of the classes and the classification itself was correct.

In the set of learning data consisting of 255 facts no wrongly classified situations were found.

In the set of testing data (table 1) consisting of 45 facts, it turned out that two situations were not classified to any of the two classes. Respectively, six and three situations were classified incorrectly as safe or dangerous ones with two situations classified at the same time to both classes. They were, therefore, analyzed in detail.

Table 1. Identification and evaluation of a navigational situation in the expert system based on the rules base – FOIL algorithm – testing data

No of situations	Situations classified incorrectly	Unclassified situations
45	9	2

Among the situations incorrectly assigned to the class i three were valued by navigators as follows: 0.56, 0.54 and 0.52, thus the values were quite close to the boundary between the two classes.

Two of these situations concerned extreme events where the recorded values of deviations from the fairway centre line were maximum and had not been entered in the learning data.

In one case (value: 0.66) the navigators presumably took account of additional factors, because the parameters essential for the evaluation do not indicate the situation was dangerous.

Three of the situations wrongly assigned to the class II obtained the following values: 0.44, 0.48 and 0.32.

Two situations were not identified at all, which is a consequence of the way the algorithm works, namely the areas of the learning data are covered exactly while other areas may be completely omitted. That is why the learning data-set should cover all the situations that may be observed.

C4.5

The results of the verification for the 2-class and 3-class division are given in tables 2 and 3. Due to the procedure of decision tree pruning the results account for learning and testing data.

Table 2. Identification and evaluation of a navigational situation in the expert system based on the decision tree – C4.5 algorithm – 2-class division.

Data	No of situations	Incorrectly classified situations
Learning	255	19
Testing	45	8
Total	300	27

Out of 24 situations incorrectly assigned to class i (17 for the learning data and 7 for the testing data) 19 situations (16 for the learning data and 3 for the testing data) were assigned by the navigators to the <0.5, 0.6> range – close to the boundary between the two classes. In the remaining cases the values were 0.70 (learning data) and 0.66, 0.74, 0.82, 0.66 (testing data).

Altogether three situations were erroneously assigned to the class II (respective values were: 0.42, 0.44 and 0.48): two for the learning data and one for the testing data. In all cases the values were close to the class boundary.

Table 3 presents the results of dividing the situations into three classes.

Table 3. Identification and evaluation of a navigational situation in the expert system based on a decision tree –C4.5 algorithm – for the 3-class division

Data	No of situations	Incorrectly classified situations
Learning	255	21
Testing	45	13
Total	300	34

Of all the incorrectly classified situations one (testing data) was classified as safe, although the navigators found it dangerous – the error that occurred in two classes – (navigators' value - 0.66). That situation was discussed above in the section concerning the FOIL algorithm (possibly additional factors were accounted for). In the remaining cases the errors consisted in classifying situations as belonging to the neighbouring class.

The summarized table below presents all the classification results for 2-class (FOIL, C4.5) and 3-class divisions (C4.5). The verification of the evaluations was performed through a comparison of classification results obtained from the various systems (comparative algorithm). The results are shown in the table 4.

Table 4. The overall results of navigational situation classifications

Data	Number of Situations	Situations classified correctly by all the classification systems	Situations classified incorrectly by one or more classification systems	Situations classified incorrectly after the comparative algorithm was applied
Learning	255	217	38	2
Testing	45	25	20	7
Total	300	232	58	9

In the case of two incorrectly classified situations from the learning data the values of navigators' assessments were close to the boundary between the two classes and amounted to 0.42 and 0.44.

Out of seven incorrectly classified situations taken from the testing data five evaluations by navigators were close to the boundary between the two classes; their respective values were 0.44, 0,54, 0.48 0.52 and 0.52. The other two wrongly classified situations were as follows:

1) situation valued at 0.66 by navigators; presumably the navigators took additional factors into account,
2) situation valued at 0.82 by navigators; a case of maximum recorded deviation from the fairway centre line which was not included in the learning data set.

The parallel application of the presented systems for evaluating a navigational situation and the verification of the classification based on a comparative algorithm allows to substantially reduce the number of errors and to increase the reliability of the expert system.

DISCUSSION

The acquisition of expert knowledge, i.e. extraction and transformation into a form of a knowledge base of an expert system has led to the creation of a tool aiding the evaluation of navigational situations.

The results obtained indicate a high degree of convergence of values generated by the expert system and actual classifications performed by navigators (Tab. 1, 2, 3).

Cases of incorrect classification have resulted from a limited number of facts – thus there is no possibility to account for all potential situations; another reason is an arbitrary division into classes, which in the case of even slight changes in criteria applied by the navigators may lead to wrong classifications of situations assessed as close to the safe / dangerous boundary.

A parallel application of knowledge bases, whose creation was based on analyzed algorithms, and introduction of the verification stage by comparing individual values (Tab.4) allow to enhance the reliability of the expert system used for the evaluation of navigational situations.

CONCLUSIONS

The article presents a methodology of acquisition and representation of expert navigators' knowledge for the identification and evaluation of a navigational situation in restricted area traffic. Chosen tools of knowledge acquisition are described. Tools are used for designing a knowledge base to suit the needs of vessel traffic service (VTS) centres. a prototype expert system for the identification and evaluation of a navigational situation in restricted area traffic is presented. The method has a capacity of updating the knowledge base of the system through supplementing the set of facts and automatic generation of logical rules or decision trees. It seems purposeful to enrich the presented expert system with tools for quantitative assessment of navigational safety, which would be based on artificial neural networks with fuzzy logic (non-symbolic representation of knowledge), as well as with a graphic display in the form of ship's fuzzy domain. These features may constitute a considerable assistance in evaluating a navigational situation by VTMS operators.

The research is in progress on methods of including other vital factors affecting the safety of navigation, such as ship's and area parameters, sea and meteorological conditions, acquisition of navigators' relevant knowledge and the implementation of the knowledge in an appropriate expert system.

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