Induction of decision rules for the collision regulations

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Abstract: The article presents problems of the transformation of knowledge codified in the COLREGs into a form which permits its use in navigational information systems. The need to develop a knowledge base in this field and implement it in an expert system supporting navigational decisions onboard ships is rational. It is a well-known fact that navigational information systems greatly support navigation and increase its safety. Examples of regulations (COLREGs rule 13 – overtaking) are interpreted, then presented as decision tables in order to check whether decision rule induction is possible from such data. Selected algorithms of rule induction are briefly described and then tested. The experiments are compared and conclusions are drawn.

Keywords: knowledge base, knowledge representation, expert system, machine learning

1. Introduction

Development of computer hardware and software technologies contributes to the growing use of computer-based solutions in all industries. In sea and inland shipping the impact of modern technologies is highly visible. Currently it is difficult to imagine shipping without help of such systems as GPS (Global Positioning System), ARPA (Automatic Radar Plotting Aid), AIS (Automatic Identification System), ECDIS (Electronic Chart Display and Information System), etc. These tools considerably improve shipping safety, enhance efficiency and reduce the risk of collision. The main task of navigation support systems currently used onboard ships is the collection, processing and presentation of information to the navigator. This is done to facilitate the operators job which is to conduct navigation safely. Use of the available navigation equipment and systems helps the navigator analyse the situation and make decisions. These, however, are subjective and may be inappropriate or wrong. There are many causes of erroneous decisions, from a lack of navigator’s experience, through insufficient co-operation among the crew members, errors in measurements and readouts to a general overload of actions required in the operation of systems and a quantity of data for interpretation [1].

Further development of computer systems used for navigation, progressing in the direction of decision-support systems, is possible by the implementation of new solutions which can extend the functionality of the systems from presentation of information to giving advice. A decision support system analyses and interprets a navigational situation, determines a solution and proposes an optimal manoeuvre. Such an approach contributes to relieving navigators of some decisions they have to make and can thus reduce the number of errors committed by human beings [2].

The analysis and interpretation of navigational situation requires that the standing regulations be taken into account. The COLREGs have been drawn up on the basis of knowledge
and experience of expert navigators. This knowledge may be processed and implemented in the navigation support information system in order to extend its functionality. COLREGs, integrated with local regulations applying to particular water areas (e.g. waterways, ports) and good sea practices, may be seen as a knowledge base for the navigator, constituting an element of navigational decision support system. Such a system would provide a correct interpretation of navigational situations, allow access to knowledge about safe sailing of ships, and minimise the subjectivity of human interpretation of the regulations.

A Navigational Decision Support System (NDSS) [3, 4] developed at the Maritime University in Szczecin is an example of the implementation of the COLREGs regulations, featuring an algorithmisation of selected regulations in the form of a binary tree. Such a form of knowledge interpretation involves some difficulties in its expansion and verification, therefore one crucial issue involved in the building of navigation-support knowledge bases is the development of method/s used for knowledge representation. As a result of the above, work on building an expert system is underway. An expert system is a computer program consisting of a knowledge base, inference engine and user interface. Optionally it may be equipped with an explaining mechanism whose role is to explain to the navigator how the expert answer given by the system was deduced. Knowledge engineering is a field dealing with the issues involved in building expert systems. It deals with the acquisition and processing of background knowledge, design and selection of appropriate inference methods and the building of interfaces [5, 6].

The main goal of this paper is to find out whether machine learning algorithms could be used for induction of decision rules for the area of navigation. Chapter 2 provides information on the analysed range of knowledge and problems regarding interpretation of regulation. Chapter 3 provides a brief overview of selected induction algorithms induction for decision rules. Chapter 4 describes the methodology of numerical experiment. Chapter 5 contains the results of the experiment, while section 6 conclusions.

2. COLREGs Interpretation

Regulations in force are a basis for an analysis and interpretation of navigational situations. Implementation of the COLREGs in a computer system is a difficult task, which stems from the characteristics of COLREGs provisions and from how they are applied. Building a knowledge base on them requires that the regulations be first correctly interpreted by an expert (navigator), and then a knowledge engineer must be involved in the implementation.

The Convention on the International Regulations for Preventing Collisions at Sea (COLREGs 1972) was signed into force in 1972 in London, and is a set of regulations which formalise the rules of mutual manoeuvring by ships, technical aspects such as the definitions of vessels, the arrangement of lights and marks, the methods of signalling and the rules for navigators conduct in specific situations. The Convention consists of five parts and appendices [7]. Part A includes the rules of Convention application, the scope of responsibility and basic definitions. Part B, divided into three sections, comprises rules referring to the conduct of ships in all visibility conditions, actions to be taken by ships seeing each other and the conduct in limited visibility conditions. The following parts refer, respectively, to: definitions of lights and shapes (part C), use of acoustic and light signals (part D) and the definitions of vessels exempted from the Convention (part E).

Part B of the Convention, supplemented by definitions from Part A, constitutes knowledge which definitely must be included in the COLREGs knowledge base. This applies in particular
to situations of ship encounters during overtaking manoeuvres, ships approaching each other on opposite courses and ships on crossing courses in good visibility conditions. The above mentioned situations of ship encounters are illustrated in Fig. 1.

Figure 1. Situations of ship encounters according to COLREGs

In accordance with COLREGs provisions the a/m ship encounters are defined in the following way [7]:

1. Overtaking (sector A in Fig.1, Rule 13). The overtaking situation takes place when the faster ship approaches the slower ship from a direction lying at more than 22.5 degrees aft of abeam. Each time the overtaking ship must keep out of the way of the vessel being overtaken.

2. Head-on (or almost head-on) course (sector C in Fig.1, Rule 14). When two power-driven vessels are meeting head-on and there is a risk of collision, both must alter course to starboard so that they pass on the port side of the other.

3. Crossing courses (sectors B and D in Fig.1, Rule 15). When two power-driven vessels are crossing, the vessel which has the other on the starboard side must give way and avoid crossing ahead of her.

Correct interpretation of the COLREGs requires a detailed analysis of particular rules. As an example, in case of Rule no.13 (overtaking), the following alternative scenarios and exceptions should be taken into account:

— An exception to the rule that each time the overtaking ship must give way is a situation, where the overtaking ship is not under command. Such a ship is partially or fully incapable of manoeuvring.

— In a doubtful situation where the navigator is not sure whether he/she is overtaking another ship, he should assume that he is and act accordingly.

— Side-to-side distance between two ships at the moment of overtaking is important during manoeuvres on parallel courses (Fig.2).
— Changes of bearing on another ship should not influence the interpretation of initial conditions, i.e. an overtaking ship will not become a ship on crossing course.

![Diagram](image)

Figure 2. Definition of distance abeam during the overtaking manoeuvre on parallel courses

As shown in the example above, the acquisition of knowledge necessary for the building of a knowledge base requires that some attributes be extracted from the regulations referring to navigational situations used for the determination of logical premises and conclusions. These, in turn, will constitute a basis for the formulation of rules. A separate problem is the accounting for other factors not directly addressed by the Convention, e.g. data contained in radar report (CPA, TCPA). A relevancy analysis should be carried out with regard to such data, to evaluate whether they should be included in the knowledge base being built.

3. Induction of decision rules

One of the most popular knowledge representation methods, widely used in the field of expert systems, is the rule-based representation of knowledge. Such a representation is simpler in interpretation for a human being than, for example, complex decision trees, and more comprehensible than knowledge 'hidden’ in neural networks. A decision rule consists of a conditional part (premise) and a decision part (conclusion). In its most general form the rule is a logical implication [6, 8]. There are many ways to present rules, one of them is shown below (1):

\[ \text{IF } X \text{ THEN } Y \]  

where: \( X \) – condition, \( Y \) – decision.

Many induction algorithms have been developed for the purpose of building decision rule sets. Depending on the type and size of data set (knowledge), expected accuracy of results and fault tolerance, different algorithms are used for the solving of various problems, being selected to suit their character and the requirements of a given field of knowledge.
One of possible solutions for the case of knowledge base containing the COLREGs is the use of rules representing knowledge in the form of examples showing specific navigational situations.

These examples will represent hypotheses subject to classification into designated categories. Then, the conditional part of the rules will specify the parameters which may be met or not by the examples. The decision part of a rule, in turn, will specify the decision class for the examples meeting the conditions specified in the hypothesis represented by a given rule.

In order to analyse the possibilities of using the algorithms for the induction of decision rules, an approach known as machine learning has been proposed. There are many methods for such learning process, but general understanding is that a learning system is a system which remembers specific information and creates relationships, based on the analysed data. Then, it may classify new, unknown objects and phenomena. Such an induction-based model of learning may be implemented by using the selected algorithms for the building of hypotheses in the form of decision rules sets, where training examples (a training set) are used for this purpose. Then, the effectiveness of decision rule sets obtained in this way may be verified on unknown examples (testing set). The experiment consisting in the induction of COLREGs decision rules has been carried out with the algorithms: AQ, CN2, C4.5Rules, LEM1 and LEM2.

The algorithms listed above are based on various methods of induction used for the sets of decision rules. The following ought to be mentioned among these methods: sequential covering procedure, rough sets theory and a method based on information theory. The algorithms AQ and CN2 are based on the sequential covering procedure, which consists in the generation of successive rules covering some number of examples from the training set, until it is fully covered. The way the conditional part of the rule is assembled is crucially important here. It should contain a complex that covers a possibly highest number of training examples while showing at the same time possibly little differentiation in their categories. Both AQ and CN2 conduct the verification of complex space from the most general to most specific. They differ however in the use of complex specialisation mechanisms and the heuristic functions used for the evaluation of their quality. During the construction of each successive rule in AQ the whole training set is used for the complex accuracy evaluation. In case of CN2 algorithm, the verification of each successive complex takes place for the training examples not covered by the previously constructed rules [8].

Another method to induce decision rules is rough sets theory. This theory provides tools for the formal representation of knowledge and is effectively used in data mining, knowledge discovery in concept classification problems, and decision-making [9]. Rough sets are a development of classical set theory, introducing new concepts such as lower and upper set approximation, as well as set regions: positive, negative and boundary. The algorithms based on rough set theory examine the relations between attributes (object properties) and determine the degree of their suitability for the description of an object. Their use enables the identification of irreducible attributes and the evaluation of decision table correctness [9]. The assumptions of rough sets theory are implemented in the algorithms LEM1 and LEM2 (among others) and their numerous modifications.

The algorithm C4.5 developed by Quinlan [10] in 1993 is used for the building of decision trees. Based on information theory, the algorithm calculates entropy for the attributes describing the examined objects. On this basis, a tree is built in successive iterations of the algorithm, starting from a node containing an attribute with the lowest entropy measure, or, using a different interpretation, having a highest information gain (C4.5 implements some modification
consisting in using a relative information gain). As an addition with regard to its predecessor, the algorithm has a capability to use continuous attributes and to classify incomplete data (with missing attributes). It also has improved classification mechanisms as well as pruning mechanisms whose purpose is to prevent excessive growth of the tree. In connection with a fact that decision trees may be transformed into decision rules, the C4.5Rules algorithm was built, its purpose being the generation of the rule classifiers. However, rules built on the basis of decision tree analysis progressing from the root to each leaf are subject to further transformations. Usually, rules containing all the conditions undergo generalisation, consisting in a deletion of one or more conditions. This causes the rules to be no more mutually disjunctive. The successive phases of the algorithm include the examination of rules for their covering of particular decision classes, and the determination of the order of rules in the set.

4. Experiment

To examine possible applications of decisions rules induction algorithms for building a COLREGs knowledge database, a numerical experiment was carried out. It consisted in generating sets of decision rules for COLREGs rule 13 (overtaking) using the induction algorithms AQ, CN2, C4.5Rules, LEM1 and LEM2.

In order to check the differences between the results obtained by particular algorithms, they were tested by using two independent data sets representing the situations of ship encounters during an overtaking manoeuvre. The first set (designated A) contained examples described by discrete (symbolic) attributes. The other set (designated B) contained examples described by discrete and numerical attributes (real numbers). Using the real number attributes in set B additionally required a discretisation of attribute values. These two types of sets were provided in order to check whether the data type has any impact on the obtained results. This applies to parameters among which the following may be mentioned: number of rules (size of rules set), length of rules (number of attributes included in the conditional part of the rules), number of attributes used and their values (general). These parameters have influence on the capability of a generated rules set to correctly classify unknown objects. Data sets provided to the experiment have been verified by a navigational expert.

Classification is a process whose task is to fit the object description to the conditional parts of decision rules. On the basis of object attribute values the object is then assigned to a particular decision class.

Data sets A and B were presented in the form of decision tables. Each example entered in the table row was a distinct object. The values of particular attributes are put in the columns of decision tables (constituting conditional attributes). The attributes listed below have been selected for the building of the sets based on the analysis of COLREGs rule no.13. Possible attribute values are given in the braces:

Set A:
- Speed \{less, equal, more\} – own ships speed relative to the other ship.
- Range>5NM \{true, false\} – abeam distance between ships, more precisely a distance between the ships at the moment of overtaking, specified as more or less than 5NM (see chapter 2).
- Course \{parallel, crossing, divergent\} – course of own ship with respect to the other ship.
- Status_dmg_S1 \{true, false\} – attribute specifying the status of own ship (whether is not under command) (see chapter 2).
- Status_dmg_S2 \{true, false\} – as above, only for the other ship.
— Action \{S1\_overtaking, S1\_being\_overtaken\} – auxiliary attribute referring to the position of own ship, i.e. astern or ahead of the other ship.

Set B
— Bearing\_S1 \{real \(< 0.0, 180.0\)\} – bearing on the other ship, in degrees.
— Bearing\_S2 \{real \(< 0.0, 180.0\)\} – bearing from the other ship on (our) own ship, in degrees.
— Speed, Range 5NM, Status\_dmg\_S1, Status\_dmg\_S2 – as in set A.

Correct classification of the examples in a table is a problem calling for a definite solution. Based on expert knowledge and Rule 13 of the COLREGs, all the objects from sets A and B have been divided into two classes. A decision attribute is used to show which class an object belongs to, with the last column in the table containing this attribute:
— Decision C1\_give\_way, C2\_stand\_on.

Summing up, decision tables A and B contain the examples (Object) described by conditional attributes (e.g. Action, Speed, Course, etc.), on the basis of which the examples have been classified (Decision). The examples where the overtaking situation does not apply have been assigned to decision class C2\_stand\_on. Example data from the sets A and B are presented in Tables 1 and 2. In order to obtain reliable results, a numerical experiment was conducted for each of the tested algorithms according to the following procedure:
1. Building of sets A and B;
2. Classification of objects included in sets A and B to decision classes;
3. Generation of training and testing subsets on the basis of sets A and B, which consisted in a random division of sets A and B in such a way that various cases could be found in a training subset and a testing subset. The division of set A and set B into a training and testing subset was done using a ratio of 90% to 10% (respectively the number of training examples and testing examples). The subsets have been designated as follows:
   — for set A: \(A'_i = \{A'_iL, A'_iT\}\)
   — for set B: \(B'_i = \{B'_iL, B'_iT\}\)
   where \(i = 1...5\)
   \(A'_iL, B'_iL\) – subsets of training examples,
   \(A'_iT, B'_iT\) – subsets of testing examples;
4. Execution of attribute value discretisation for the subsets created from data set B.
5. Execution of training (rule induction) on the basis of subsets \(A'_iL, B'_iL\);
6. Testing of the obtained sets of rules by using sets \(A'_iT, B'_iT\);
7. Analysis of results – averaging of the obtained values for five tests executed on sets A and B, for: number of rules, length of rules, classification accuracy (classification error).

Table 1. Decision table for data set A
<table>
<thead>
<tr>
<th>Object</th>
<th>Action</th>
<th>Speed</th>
<th>Range (\geq 5\text{NM})</th>
<th>Course</th>
<th>Status_dmg_S1</th>
<th>Status_dmg_S2</th>
<th>Decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>S1_overtaking</td>
<td>more</td>
<td>false</td>
<td>parallel</td>
<td>false</td>
<td>false</td>
<td>C1_give_way</td>
</tr>
<tr>
<td>2</td>
<td>S1_overtaking</td>
<td>more</td>
<td>false</td>
<td>parallel</td>
<td>true</td>
<td>false</td>
<td>C2_stand_on</td>
</tr>
<tr>
<td>3</td>
<td>S1_overtaking</td>
<td>more</td>
<td>false</td>
<td>crossing</td>
<td>false</td>
<td>false</td>
<td>C1_give_way</td>
</tr>
<tr>
<td>4</td>
<td>S1_overtaking</td>
<td>more</td>
<td>false</td>
<td>crossing</td>
<td>true</td>
<td>true</td>
<td>C2_stand_on</td>
</tr>
<tr>
<td>…</td>
<td>S1_being_overtaken</td>
<td>equal</td>
<td>false</td>
<td>crossing</td>
<td>true</td>
<td>true</td>
<td>C1_give_way</td>
</tr>
<tr>
<td>142</td>
<td>S1_being_overtaken</td>
<td>less</td>
<td>true</td>
<td>crossing</td>
<td>true</td>
<td>true</td>
<td>C2_stand_on</td>
</tr>
<tr>
<td>143</td>
<td>S1_being_overtaken</td>
<td>less</td>
<td>true</td>
<td>divergent</td>
<td>false</td>
<td>true</td>
<td>C2_stand_on</td>
</tr>
<tr>
<td>144</td>
<td>S1_being_overtaken</td>
<td>less</td>
<td>true</td>
<td>divergent</td>
<td>true</td>
<td>true</td>
<td>C2_stand_on</td>
</tr>
</tbody>
</table>
Table 2. Decision table for data set B

<table>
<thead>
<tr>
<th>Object</th>
<th>Bearing_S1</th>
<th>Bearing_S2</th>
<th>Speed</th>
<th>Range &gt;5NM</th>
<th>Status_dmg_S1</th>
<th>Status_dmg_S1</th>
<th>Decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.00</td>
<td>180.00</td>
<td>more</td>
<td>false</td>
<td>false</td>
<td>false</td>
<td>C1_give_way</td>
</tr>
<tr>
<td>2</td>
<td>5.00</td>
<td>147.50</td>
<td>more</td>
<td>false</td>
<td>true</td>
<td>false</td>
<td>C2_stand_on</td>
</tr>
<tr>
<td>3</td>
<td>5.00</td>
<td>180.00</td>
<td>equal</td>
<td>false</td>
<td>false</td>
<td>true</td>
<td>C2_stand_on</td>
</tr>
<tr>
<td>...</td>
<td>55.00</td>
<td>122.50</td>
<td>equal</td>
<td>false</td>
<td>true</td>
<td>false</td>
<td>C2_stand_on</td>
</tr>
<tr>
<td>1728</td>
<td>50.00</td>
<td>117.50</td>
<td>less</td>
<td>false</td>
<td>true</td>
<td>false</td>
<td>C2_stand_on</td>
</tr>
</tbody>
</table>

5. Results

The results obtained for the algorithms tested on sets A and B have displayed significant differences (see Table 3), which applies to the number of induced rules and average length of rules. For the data from data set A, classification accuracy was on about the same level for both training data and testing data. The algorithms LEM and AQ have executed the classification of training examples with accuracy equalling respectively 100% and 99%. These algorithms have built most numerous sets of rules. C4.5Rules algorithm has built the rule sets about 38% shorter than the above algorithms, maintaining a nearly identical accuracy of example classification. In that case the rules contained on average fewer conditions.

The CN2 algorithm generated the shortest rule sets (6.4 rules per a subset), which contained on average 1.87 attributes per rule, but it has achieved a worse classification result. The LEM1 algorithm, in spite of correct classification of training examples, has shown a highest classification error for testing examples, which amounted to 74%. The experiment carried out on the data from set B has shown a higher diversity of results. The training datasets were in this case more numerous (1,555 examples) and included numerical attributes.

The attribute quantization process has been observed to bring about the appearance of duplicate examples, in both training set and testing set, which has negatively affected the classification results of the algorithms CN2, LEM1 and LEM2.

The CN2 algorithm obtained the poorest result of classification over testing examples, equalling 78%, while LEM algorithms, due to duplicate examples, generated sets of certain and possible rules. Only the sets of certain rules were used for the classification of examples, but nonetheless the classification error was higher than the one obtained in case of C4.5Rules and AQ algorithms.

The C4.5 Rules algorithm which is able to use embedded quantization mechanisms achieved the best result for numerical data. Due to duplicates, the so-called overfitting of algorithm

Table 3. Results of experiment for sets A and B

<table>
<thead>
<tr>
<th>Set A (averaged)</th>
<th>C4.5Rules</th>
<th>AQ</th>
<th>CN2</th>
<th>LEM1</th>
<th>LEM2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of examples:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>total / training / testing</td>
<td>144 / 129 / 15</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of rules</td>
<td>12.4</td>
<td>21.4</td>
<td>6.4</td>
<td>20.4</td>
<td>18.2</td>
</tr>
<tr>
<td>Rule length</td>
<td>3.12</td>
<td>3.59</td>
<td>1.87</td>
<td>3.44</td>
<td>3.38</td>
</tr>
<tr>
<td>Classification accuracy:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>training / testing data</td>
<td>0.965 / 0.891</td>
<td>0.998 / 0.918</td>
<td>0.860 / 0.864</td>
<td>1.0 / 0.735</td>
<td>1.0 / 0.859</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Set B (averaged)</th>
<th>C4.5Rules</th>
<th>AQ</th>
<th>CN2</th>
<th>LEM1</th>
<th>LEM2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of examples:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>total / training / testing</td>
<td>1728 / 1555 / 173</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of rules</td>
<td>29</td>
<td>74.2</td>
<td>10.4</td>
<td>166</td>
<td>96</td>
</tr>
<tr>
<td>Rule length</td>
<td>3.08</td>
<td>4.11</td>
<td>1.89</td>
<td>3.85</td>
<td>3.82</td>
</tr>
<tr>
<td>Classification accuracy:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>training / testing data</td>
<td>0.977 / 0.961</td>
<td>0.973 / 0.960</td>
<td>0.782 / 0.780</td>
<td>0.948 / 0.826</td>
<td>0.948 / 0.907</td>
</tr>
</tbody>
</table>
took place, likely leading to higher classification error than would be possible otherwise. It was also observed that the distribution of examples in a training set and a testing set is also responsible for classification errors. Erroneously classified examples showed no repetition both for consecutive subsets within a single algorithm, and for the tested algorithms. Some excerpts from rule sets generated by tested algorithms using data from set A are presented below:

C.45Rules

if(course=intersect && action=S1_overtakes && status_dmg_S2=true && speed=more) (4/4) output=C1_you_are_give_way_vessel
else if(course=intersect && status_dmg_S1=false && speed=more && action=S1_overtakes) (4/4) output=C1_you_are_give_way_vessel (...)

AQ

Rule 14: IF speed <> 0.0 AND course = 0.0 AND action = 0.0 THEN decision -> C2_you_are_stand_on_vessel [ 0 8]
Rule 15: IF action <> 0.0 AND course <> 1.0 AND status_dmg_S2 = 1.0 THEN decision -> C2_you_are_stand_on_vessel [ 0 7]

CN2

Rule 1: IF course <> 2.0 AND range>_5Nm <> 1.0 THEN decision -> C2_you_are_stand_on_vessel [ 0 42]
Rule 2: IF status_dmg_S2 = 1.0 AND action <> 0.0 THEN decision -> C2_you_are_stand_on_vessel [ 0 22]
Rule 3: IF course = 1.0 THEN decision -> C2_you_are_stand_on_vessel [ 0 15] (...)

LEM1

(action,S1_overtakes) & (speed,more) & (course,intersect) &
(status_dmg_S1,false) -> (decision,C1_you_are_give_way_vessel)
(course,divergent) -> (decision,C2_you_are_stand_on_vessel) (...)

6. Conclusions

Correct functioning of a decision support system requires a correct interpretation of COLREGs rules – the classification of ship encounters has to be in compliance with applicable rules, so that the navigators concerned will know their responsibilities. This requires that a proper knowledge base be developed. Research was conducted into opportunities offered by machine learning methods used for the induction of decision rules drawn from the COLREGs. A numerical experiment was carried out, consisting in the induction of rules on the basis of training data and then testing the obtained rule sets on sample testing data. The analysis of results proved that in case of set A (symbolic attributes) only the algorithms LEM1 and LEM2 provided a correct classification of training examples. In case of set B (symbolic and numerical attributes), no algorithm was able to obtain a correct result with the training examples.

The testing process (application of rules to testing data) has shown that no rule set generated using the algorithms in question has been able to correctly classify all the testing data. The best results were obtained for set A testing examples by the algorithms AQ and minimally inferior C4.5Rules. In case of classification of examples based on set B, C4.5Rules attained an insignificantly better result than AQ. A likely cause of such results obtained for set B is the
selection of discretisation method for numerical values. In C4.5Rules a dynamic method was used to analyse the mutual relationships between attributes during the building of a classifier. The remaining algorithms used a static method – numerical values were divided into intervals before the training and testing process. It should be noted that all of the tested algorithms did not meet expectations for the classification of examples – having regard to the relationship between the training and test examples. It is obvious that the creation of proper set of decision rules for ship navigation requires the correct classification of both training and test examples. In addition, it is important that the decision rules knowledge base should also take into account the true nature of navigation. It should consider (solve) one to one meeting events as well when it comes to meeting with many ships at the same time.

As a result, further analysis is needed to unequivocally determine whether the tested algorithms could be used for the building of COLREGs knowledge base. Possibilities of algorithm modification as well as searching for new solutions and/or developing them should be examined. The analysis should also be applied to other data forms and alternative methods of knowledge representation.

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References