



A Novel Case Knowledge Representation Model for Maritime Collision Accidents

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Abstract. It is of great significance to research a method to standardize the management of maritime collision case knowledge with high complexity, poor standardization and weak regularity. In this paper, a novel case knowledge representation model is proposed based on ontology and convolution neural network. Firstly, an automatic case knowledge extraction model is proposed, which can be used to improve the efficiency of knowledge extraction. Secondly, under the condition of extracting case knowledge, a case knowledge representation model is proposed based on improved ontology, which can be used to improve the scientific and standardized case knowledge management. Finally, the effectiveness of the proposed is illustrated by a case study based on maritime collision accident in the South China Sea.

Keywords: Knowledge representation, Ontology, Convolution neural network

1 Introduction

Case-based reasoning(CBR)^[1-3] is a very effective emergency decision making method based on artificial intelligence, Case representation is the premise of case-based reasoning(CBR)^[4-5], the efficiency of emergency decision based on CBR can be influenced by the case presentation directly. Therefore, It is crucial to propose a novel case knowledge representation model to improve the efficiency of emergency decision.

Knowledge representation methods mainly include frame representation, object-oriented, logical predicates, ontology model, and so on.

Among them, Hommen^[6] proposed a knowledge representation method based on the frame representation method, but the method is not good at expressing process knowledge; Walczak^[7] proposed a knowledge representation method based on object-oriented. It can be shown that the completeness of the object-oriented method is poor from the research; Yang^[8] established the knowledge representation model based on logical predicates method, it can be seen that the logical predicates are difficult to express uncertain knowledge and heuristic knowledge, and have low computational efficiency. Gregor^[9] presented a knowledge representation method based on the ontology, the ontology model has the advantages of clear concept and accurate expression of

attribute relation, it can be used to represent dynamic knowledge and the relationship between concepts or attributes.

Above all, it is not difficult to know that ontology model is more excellent in knowledge representation than knowledge representation model. The case knowledge of collision accidents^[10] is characterized by weak regularity, poor standardization, and high complexity. With the advantages of strong knowledge representation completeness and applicability to dynamic knowledge representation of ontology, the case knowledge representation model based on ontology is constructed to address the problem of the fuzzy hierarchical relationship of case knowledge. Therefore, the ontology can be used to establish a case knowledge representation model in this paper.

At the same time, considering the characteristics of complex knowledge and logical relations in historical cases of collision, Manual extraction of case knowledge will lead to problems such as high cost of ontology construction time and strong subjectivity of concept extraction. Therefore, it is necessary to realize the automatic extraction of ontology concepts and relations based on natural language processing technology and deep learning method.

In summary, a novel case knowledge representation model based on ontology and convolutional neural network should be proposed in this paper.

2 Modelling

2.1 The Establishment of Case Knowledge Extraction Model

In order to extract the relationships between concepts of ontology automatically. The logical relation extraction model based on convolutional neural networks and attention mechanism is proposed in this paper. At first, text data pre-processing is performed based on Jieba word segmentation tool. Afterwards, the results of word segmentation can be transformed into word vector form based on word vector model, and sentence features can be learned based on convolutional neural network. Finally, this feature can be used for the input of softmax classifier, and the output result of relationship can be obtained.

In the feature fusion process of head entity and sentence vector, it can be considered that the influence of the head entity feature on the tail entity labelling operation is mainly related to the current position word. Therefore, the attention mechanism can be added in the process of feature fusion, which can be combined with the convolution neural network method to improve the accuracy of entity labelling. The specific steps of head entity and tail entity extraction based on attention mechanism are as follows.

(1) Determination of feature vector of head entity

Firstly, the word feature vector of head entity can be represented as X_{head} . Afterwards, X_{head} are input into a multi-layer CNN network to obtain entity feature, and the head entity feature vector can be obtained based on the maximum pooling operation as shown in Eq. (1).

$$x_{head} = MaxPooling(CNN(X_{head})) \quad (1)$$

(2) Determination of feature vector of the sentence

Firstly, the attention weight can be calculated based on the sentence vector and the head entity feature vector. Secondly, the attention weight can be combined with the head entity feature vector to obtain the weighted head entity vector. Thirdly, the weighted head entity vector and the word vector of the current position can be spliced together. Consequently, the sentence vector that incorporates the characteristics of the head entity can be expressed as $T = \{T_1, T_2, \dots, T_n\}$, the feature fusion process is shown in Eq. (2).

$$T_i = [X_i; (X_i^T x_{head})x_{head}] \quad i = 1, 2, \dots, n \quad (2)$$

Where T_i stands for the feature vector of i -th word based on feature fusion, X stands for the sentence vector, x_{head} stands for head entity feature vector.

(3) Determination of the tail entity

The relationship and tail entity labelling can be obtained based on the multi-layer binary classifier. In the process of tail entity labelling, several relationships should be predefined at first, and the number of relationships is consistent with layers of the binary classifier. The input of the binary classifier is the sentence vector that integrates the characteristics of the head entity, and the sentence vector can be decoded as shown in Equations (3) and (4). For all possible relations, the corresponding tail entity for each detected head entity can be marked by the classifier simultaneously.

$$P_i^{o-start} = \sigma(\mathbf{W}_{start}^o T_i + b_{start}^o) \quad (3)$$

$$P_i^{o-end} = \sigma(\mathbf{W}_{end}^o T_i + b_{end}^o) \quad (4)$$

Where the output value of the i -th feature vector after processing by the decoding layer can be represented as $P_i^{o-start}$ and P_i^{o-end} respectively, \mathbf{W} stands for the weight matrix, b stands for the bias value, tail entity can be represented as o , and sigmoid activation function can be represented as σ .

Finally, the head entity, sentence feature vectors, and tail entity can be extracted as the input of the softmax classifier based on the above method. The entity relationship confidence ranking in historical cases of collision accidents can be obtained based on the classifier, and the entity relationship with high confidence is selected to provide an effective reference for construction of ontology automatically.

2.2 The Establishment of Ontology Model

The effect of case knowledge representation can be influenced by the structure of the ontology model. Existing ontology models include triple, quadruple, and five-tuple models. Among them, there is a lack of description of relationships between concepts in triples, there is a lack of the consideration of attributes and the feature description in the quadruple, there are concepts, attributes, and relations in the five-tuple model, the model performs well in complete representation of knowledge, but still lacks the hierarchical description of knowledge.

Therefore, in order to improve the hierarchical management and description of case knowledge, the existing five-tuple can be improved to build an ontology model for

collision accidents, which is composed of module classes, concept attributes, logical relations, constraints, and instances. The module class can be defined in ontologies, and the various modules can be managed by module class, several conceptual attributes and logical relations can be managed by each of module.

Four ontologies can be constructed according to analyzing the knowledge of historical cases in this paper, which are sea environment ontology, emergency target ontology, emergency force ontology, and emergency solution ontology respectively, and an ontology set can be proposed to manage these ontology models. S stands for the set of ontology as follows.

$$S = \{SE, ET, EF, ES\}$$

Among them, SE stands for the sea environment ontology, ET stands for the emergency target ontology, EF stands for the emergency force ontology, and ES stands for the emergency solution ontology. Each of the collision accidents ontology model can be expressed as follows.

$$CAEO = \langle M, P, L, R, I \rangle$$

Among them, M stands for a set of module classes, P stands for a set of conceptual attributes, L stands for a set of logical relations, R stands for rules, and I stands for instances.

The different ontologies can be connected by logical relationships to manage case knowledge scientifically. The logical relationship between ontologies is shown in Figure 1.

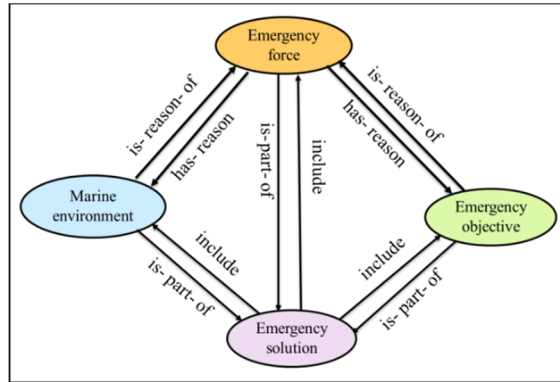


Fig. 1. Logical relationship between ontologies

As shown in Figure 1, a complete case knowledge representation model can be established based on the interaction between different ontologies, and marine environment ontology, emergency force ontology, emergency target ontology, and emergency solution ontology are included the case knowledge representation model in Figure 1. Consequently, the case knowledge with complex logic relationship and ambiguous concept can be standardized management. The knowledge representation model of collision case can be demonstrated as follows.

$$CAKP = \{S, P, L, R, I\}$$

3 Case Study

The proposed model can be applied to a real collision accident in the South China Sea, which was caused by a collision between a bulk carrier and a container ship.

Firstly, the entity relationship extracted results of historical cases are shown in Figure 2. Different colored curves represent sentences of the case respectively, the entity relationship of sentence can be determined according to the curve with the highest relationship confidence.

Secondly, the ontology set of historical collision accident can be constructed based on the proposed case knowledge representation model, and the visualization result of ontology set is shown in Figure 3.

The proposed model can be used to standardize the management of emergency decision plans. In order to verify the validity of the proposed model, the emergency decision plans can be represented by the proposed model and traditional text represented method. Emergency decision plans are retrieved using different represented methods. The comparison results of case retrieval are shown in Table 1.

Tab.1. The comparison results of case retrieval

Method	Retrieval time	Accuracy
Text represented method	15 minute	Seventy-eight percent
Proposed model	8 minute	Eighty-three percent

It can be seen that the emergency decision plans can be retrieval based on two different methods, the time and accuracy of retrieval is different. Compared with traditional text storage method, the efficiency of emergency decision makers' retrieval of emergency plans is increased by about forty-six percent, and the accuracy of retrieval based on proposed model is five percent higher than other method.

The method proposed in this paper can be used to reduce the time of manually extracting case knowledge and improve the efficiency of building case knowledge representation model. It can be seen that the case knowledge can be managed more scientifically and normally from Figure 3. The effectiveness and feasibility of the proposed model can be illustrated by the case.

4. Wang, Y., Fei, L., Feng, Y., Wang, Y., Liu, L. (2022). A hybrid retrieval strategy for case-based reasoning using soft likelihood functions. *Comput.* 26: 3489–3501. <https://doi.org/10.1007/s00500-022-06733-5>.
5. Ma, W. X., Wang, D. L. (2017). Emergency decision — making model of emergency environmental accidents based on case — based reasoning. *J. Safety Sci and Tech.* 13: 85-90. 10. 11731 /j. issn. 1673 — 193x. 2017. 12. 013.
6. Hommen, D. (2020). Ontological commitments of frame-based knowledge representations. *Synthese.* 196: 4155-4183. <https://doi.org/10.1007/s11229-017-1649-8>.
7. Walczak, S. (1998). Knowledge acquisition and knowledge representation with class: the object-oriented paradigm. *Expert Syst. Appli.* 15: 235–244. [https://doi.org/10.1016/S0957-4174\(98\)00058-X](https://doi.org/10.1016/S0957-4174(98)00058-X).
8. Yang, K.H., Olson, D., Kim, J. (2004). Comparison of first order predicate logic, fuzzy logic and non-monotonic logic as knowledge representation methodology. *Expert Syst. Appli.* 27: 501–519. <https://doi.org/10.1016/j.eswa.2004.05.012>.
9. Gregor, D., Toral, S., Ariza, T., Barrero, F. R. (2016). A methodology for structured ontology construction applied to intelligent transportation systems. *Comput. Stand.* 47: 108–119. <https://doi.org/10.1016/j.csi.2015.10.002>.
10. Wu, B., Zhao, C., Yip, T.L. (2021). A novel emergency decision-making model for collision accidents in the yangtze river. *Ocean. Eng.* 223: 108622. <https://doi.org/10.1016/j.oceaneng.2021.108622>.

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