RECOGNITION OF EMERGENCIES USING ARTIFICIAL NEURAL NETWORKS

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Abstract
An approach to decision support in emergencies by Case Based Reasoning is considered. Methodological aspects of classification the natural – language cases’ description based on linguistic analysis of subject area are under discussion. Efficiency of different classification methods are compared. The method of emergency classification by neural network training is proposed.

Introduction
If any emergency occurs while managing a complex object it causes a complete pattern (German, “gestalt”) in manager’s (operator’s) consciousness requiring some answer, a regulating reaction. Such a feature of the human mind makes it possible to have the most successful experience in readiness in past to consider the situation and to draw logical conclusions in time deficiency. To get the additional information facilitating comprehension of a problem, a man draws an analogy with precedents in the past. To ensure the most adequate response to the arisen situation, the man needs decision support on the basis of management experience in the past. Information on the past experience is accumulated in precedent base and if any new emergency occurs the decision is concluded using Case Based Reasoning (CBR). To overcome the difficulties caused by processing uncertain (fussy) knowledge on emergencies, the concept of “soft computing” is used [1].

The basic components of “soft computing” are the theory of neural networks, fuzzy logic and genetic algorithms. All these methods are based on the idea of increasing the completeness and quality of knowledge combining the facts and using meta-knowledge about the opportunities of combining the facts. While analysing the knowledge, the “soft” computing allows to formalize discrepancy and incompleteness of the information on emergencies. In the considered subject domain the most important feature of artificial neural networks is their ability to output the non – degraded pattern of the object even using incomplete or fussy data, because it simulates flexibility of human intellect that is capable to make a decision in spite of the lack of information.

Therefore, the algorithm of the nearest case retrieval uses the method of recognition based on artificial neural networks. Emergency recognition is one of the most complex problems while managing dynamic objects in emergencies.

The statistical methods of classification use rather bulky procedures, including the estimation of distribution properties of the casual attributes and the factor analysis. In practice, the implementation of this procedures causes some difficulties due to strict time-limits to make a decision in emergency, even if high-efficiency computing tools are used. The problem of finding the effective methods to analyse the emergencies has resulted in the task of recognition emergencies using artificial neural networks. The artificial neural network is a set of processing items (artificial neurons) structured into layers. Data driven information processing that brings to the pattern classification, is used both in artificial neural networks and in genetic algorithms. In this case, all the components of the "stimulus" pattern are summed up and allow to identify the object in the whole. The “top – down” principle in information processing is used by logic conclusion machines of the majority of deductive expert systems.

1. Propounding of classification task
Assuming that it is possible to decompose the set of attribute values of emergencies, defined as $X^c$ into not crossed subsets appropriate for the classes of emergencies we get the following formula:
\[ X^e = \bigcup x_i, x_j, x_j \neq x_i \]

Every class corresponds to the defined management decision \( d_i \), i.e. it is possible to conclude that \( \Psi: x^e \Rightarrow W \), where \( \forall (X, t) \in X^e \exists (w_j \in W; \Psi(X(t)) = w_j) \), and \( Y : w_i \leftarrow d_j \). Here \( X(t) \) – vector of attributes of the emergency characterising the change of \( S(t) \), \( \Theta(t) \), and \( \Omega(t) \), so that \( S(t) \in G; W = \{w_i, w_2, \ldots, w_m\} \) are the set of emergency classes. Recognition of emergency is to ascribe it to a certain emergency class on the basis of measurement and analysis of the attribute vector \( X(t) \) thereby defining the decision \( d_i \) and management influences vector \( U(t) \).

The qualitative representation of emergency attributes that is given in natural language description of emergency is characteristic to the discussed object classes. Therefore, it is necessary to decompose original set \( W \) of emergencies into \( M \) classes so that to get semantically close description groups for prompt retrieval of the necessary decision and starting the realisation of scenario to solve the problem.

2. The information space of classification attributes formation

First, to solve the problem of classification it is necessary to form the space of classification attributes. Because there are no other classification criteria that have been given a priori it is suggested to single out a set of attributes-descriptors on the basis of linguistic analysis of \( W \) natural-language emergency descriptions [3].

On the first stage of linguistic analysis, the totality of \( W \) is taken as united information resource. Applying the methods of textual, syntactical and morphological analysis to it makes it possible to single out a certain set of verbal information elements-descriptors that are important from the point of view of an individual concept to represent the sense of emergency description in the framework of the problem domain.

At first, automatically the set of descriptors \( T = \{t_1, \ldots, t_n\} \) is formed by means of text analysis programs. Then the set is expanded by concepts that have been defined by object-oriented analysis of emergency management process and then can be modified by experts.

The obtained set of descriptors serves as a necessary set of element to index text descriptions of emergencies. Indexing of \( W \) set makes it possible to describe each element \( w \) using the set of descriptors, i.e. \( w_j = (t_1, t_2, \ldots, t_n) \), where each element \( t_j \in \{0;1\} \) is a weight coefficient \( w_i \) of each concept in emergency description.

As a result of full indexing of the set of \( W \) descriptions we get a matrix “concept – emergency description” \( S = \{t_j\}, i = 1, \ldots M; j = 1, \ldots N \).

The fragment of a matrix is shown in table 1.

<table>
<thead>
<tr>
<th></th>
<th>T_1</th>
<th>T_2</th>
<th>T_3</th>
<th>T_4</th>
<th>T_5</th>
<th>T_6</th>
<th>T_7</th>
</tr>
</thead>
<tbody>
<tr>
<td>D_1</td>
<td>0.88</td>
<td>0.00</td>
<td>0.62</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.11</td>
</tr>
<tr>
<td>D_2</td>
<td>0.16</td>
<td>0.23</td>
<td>0.58</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>D_3</td>
<td>0.24</td>
<td>0.45</td>
<td>0.00</td>
<td>0.49</td>
<td>0.00</td>
<td>0.10</td>
<td>0.00</td>
</tr>
<tr>
<td>D_4</td>
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<td>0.28</td>
<td>0.58</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>D_5</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.11</td>
<td>0.00</td>
<td>0.87</td>
</tr>
<tr>
<td>D_6</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.96</td>
<td>0.15</td>
<td>0.00</td>
</tr>
<tr>
<td>D_7</td>
<td>0.26</td>
<td>0.00</td>
<td>0.00</td>
<td>0.21</td>
<td>0.00</td>
<td>0.54</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Table1 – The fragment of a matrix “concept – emergency description”

Here \( t_{ij} \) is the weight of \( i \)-th descriptor in \( j \)-th emergency description. The matrix \( S \) has some redundancy, because some of the attributes may be correlated and therefore non-informative for the classification purposes. Singling out the important concepts by the traditional methods of applied linguistics (for instance, singling out of the concepts by their occurrence frequency) turned out to be unsuccessful, because most of concepts have low occurrence frequency in a short emergency message.

Therefore, additional attribute space reduction is made by factor analysis toolbox using SPSS 10.0. The modified matrix “concept – emergency description” is basic to make emergency classification.

3. Classification of emergency descriptions by statistical analysis toolbox

The main difficulty while conducting the classification by means of statistical analysis is to choose the “right” metrics and measure of distance that helps to get more or less homogeneous and co-dimensional emergency classes. That is why, different metrics and distance combinations have been compared. The most acceptable results were got using the Dice coefficient.

\[ \beta_{ij} = \frac{2n_{ij}}{2n_{ij} + q_{ij}} \]

where \( n_{ij} \) – the number of coincidences in attributes of \( i \)-th and \( j \)-th emergency descriptions accordingly, \( q_{ij} \) – the total number of non-coincidences in attributes. Dice coefficient doubles the weight of coinciding attributes and therefore, is suitable for defining similarity of emergency descriptions. Cluster analysis was carried out by means of hierarchical classification.

The original set of \( W \) descriptions is split into \( M \) pre-defined classes. The homogenous and having approximately the same dimension (see the dendrogram in the figure 1)
4. Classification of emergency descriptions by neural network training toolbox

The main drawback and the main advantage of neural networks is their ability to be trained. In order to train a neural network to correctly recognise the classes it is necessary to have a large amount of reliable training cases that are a cut above the number of used classification attributes. But if you succeed in choosing weight coefficients of the network and reaching the acceptable error rate in training, then it is able to classify the most correctly and to take into account the features that cannot be fully interpreted in the terms of mathematics.

For training a neural network, the table $\Psi$ of independent cases of emergency descriptions from different classes (the training set of cases) is selected.

$$\{w_i, t(w_i), d(w_i)\}_{i=1}^{K}$$

where $K$ is the number of cases, $d(w_i) \in \{1, \ldots, M\}$ – expert estimation on relation of $w_i$ to one of the $M$ decision classes. In order to classify emergency descriptions the original set from matrix $S$ was divided in proportion 2:1:1 to training, testing and verifying subsets. Using these cases the network was trained at the error rate of 0.0098, 0.0063, 0.0042 for training, testing and verifying subsets accordingly. 3-layer perceptron network structure was trained (see fig.2), with $N$-neurones in input layer equal to the number of attributes-descriptors, $M$-neurones in output layer equal to number of classes of emergencies and $(N+M)/2$ neurones in the hidden layer.

Such a structure makes it possible to build a network of middle complexity that is usually recommended as the base structure [2]. Having unsuccessful training, several neurons are usually added to the hidden layer.

For recognition 50 new cases have been given to the trained network, only once the network couldn’t recognise the new case, and only once there have been some discrepancy between output results of the neural network and expert estimation. Reliability at 0.96 proves the effective training of the neural network.

5. Analysis of the classification results

The classification have been independently conducted by two different methods – by the method of statistical classification using Dice metrics and the algorithm of hierarchical clustering and by the method of training the neural network. The identical original set of emergency descriptions was used. The whole set included 150 cases in municipal-housing management, 50 new cases had to be classified into 5 pre-determined emergency classes.

According to the results of the emergency classification conclusions about the efficiency of classification by each of methods were made on the basis of attributes-descriptors. As the standard to estimate the quality of classification, the classes suggested by an expert of the subject area were adopted.

The obtained results are shown in the table 2.

<table>
<thead>
<tr>
<th></th>
<th>Expert estimation</th>
<th>Neural network</th>
<th>Statistical analysis (SPSS 10.0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>The quality of classification</td>
<td><strong>100%</strong></td>
<td><strong>96%</strong></td>
<td><strong>54%</strong></td>
</tr>
</tbody>
</table>

Table 2. – The results of classification quality estimation
Conclusion

According to the obtained results it can be concluded that the methods of statistical classification can’t give acceptable results of classification quality estimation due to the specific features of the classification task and the data used. However, the tools of statistical analysis can be used to solve auxiliary tasks, for instance, to singe out redundant input data and to reduce classification attributes’ space dimension.

The method of neural network training for solving the problems of emergency classification on the basis of their natural language description turned out to be efficient if trained using reliable expert data and makes it possible to correctly follow the expert’s logic. However, the task has to be solved within the limits that arise due to the necessity to have a large pre-determined set of qualitative training cases.

References

2. A. I. Galushkin, Modern tendencies in developing neuro-computer technologies in Russia / / Open Systems. –1997. - No.4