Knowledge Reduction Model of Crowd Evacuation Stability Based on Rough Set Theory

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Abstract. To reduce the redundant knowledge discovered from the evolution of crowd evacuation in case of emergencies, this paper aims at knowledge reduction model of crowd evacuation stability evolution. First, the evolutionary mechanism of evacuation stability state is analysed from the perspective of knowledge engineering, and the characteristics of evacuation scenario elements such as physical properties of crowd, structure of evacuation scenario and psychological behaviour of evacuees are analysed and extracted by using self-organizing mapping network algorithm; Secondly, the evolutionary characteristics of evacuation scenario elements and evacuation stability state are discretized and mapped to conditional attributes and decision attributes in rough set universe respectively. Thereby a knowledge representation method of evacuation stability evolution mechanism based on rough set decision information table is constructed. Then, the improved attribute reduction algorithm based on discernibility matrix is used to reduce the knowledge of decision information table processed by self-organizing network algorithm. Finally, a knowledge reduction model of crowd evacuation stability based on rough sets is proposed. It is validated effective to achieve the decision-making of crowd stability, and which provides theoretical basis and methodological support for scientific guidance of emergency evacuation.

1. Introduction
Crowd evacuation is a complex process under emergency conditions. Crowd evacuation stability decision-making belongs to the category of crisis decision-making. It has the characteristics of uncertain information, incomplete and semi-structured decision-making. However, it requires decision-makers (or decision information systems) to make emergency decision in time. It is a typical uncertainty and timely decision-making problem and requires decision-makers to have big amount of decision-making knowledge [1]. While the conventional decision-making knowledge based on experience summarization method has obvious subjectivity and time-space limitations, which cannot fundamentally solve the problems of dependence on experience, inconsistency of expression and lack of knowledge for evacuation stability decision-making knowledge [2].

Therefore, this paper analyses the evolutionary mechanism of crowd stability state from the perspective of knowledge engineering. We deeply analyze and extract the characteristics of evacuation scenario elements such as physical properties of crowd, structure of evacuation scenario and psychological behavior of evacuees, and the evolutionary characteristics of crowd stability state. Continuous attributes are discretized to form a knowledge representation paradigm of rough set theory.
by using self-organizing map (SOM) network. The knowledge acquisition problem is transformed into the rule generation problem of rough set theory. Because there are many characteristic factors affecting the stability of crowd evacuation, this paper uses the improved attribute reduction algorithm based on discernibility matrix to reduce the knowledge of rough set decision information table, which much efficiently contribute to the intelligent evaluation of crowd evacuation stability.

2. Rough Set 2-D Decision Table Construction

The factors affecting the stability of large-scale crowd evacuation are complex. Through evacuation scenario investigation and data analysis, the factors affecting the stability of crowd evacuation are roughly divided into two categories, they are the evacuation scenario features and the evolutionary characteristics of crowd stability state, the details in table 1.

| Characteristics of Scenario Elements | Stability Characteristics of Crowd Evacuation |
|-------------------------------------|----------------------------------------------|
| **Disaster Models:** Fire, Earthquake, Terrorist attack, etc. | Unstable Probability, Unstable Range |
| **Environmental Facilities:** Indoor, Outdoor, Transportation Hub, Obstacle Distribution, etc. | Stampede Probability |
| **Psychological Features:** Nervousness, Panic, Excitement, Despair, Dementia, etc. | Evolutionary direction, mode, velocity |
| **Physiological and Social Characteristics:** Age, Gender, Disability, Flexibility, Weight, Strangeness, etc. | Evacuation Time |
| **Behavioural Characteristics:** Herd, Light, Homing, Unconventionality Action, etc. | Casualty rate |

In this paper, we use the automatic clustering model based on Self-Organizing Mapping Network (SOM) to realize the discretization of continuous attributes. Evacuation scenario features and evacuation stability state evolutionary characteristics of crowd evacuation are mapped to conditional attributes and decision attributes of rough set domain objects, respectively. The knowledge of evacuation stability state evolution mechanism is acquired with rough set theory. A knowledge representation model for the evolution mechanism of evacuation stability state is proposed in the form of rough set 2-D decision table.

SOM (Self-organizing feature map) network was proposed by Professor Kohonen in 1981. SOM network simulates the function of self-organizing feature mapping of human brain and is a kind of learning network without supervision\[^3\]. Self-organizing feature mapping (SOM) network is a competitive learning network, which can conduct self-organizing learning without supervision\[^4\]. SOM network can learn not only the distribution of input vectors, but also the topological structure of input vectors. It is very suitable for clustering input elements.

The network can map arbitrary input patterns into one-dimensional or two-dimensional discrete graphs and keep their topological structure unchanged. The statistical characteristics of input patterns can be reflected by connecting the weight vector space.

According to reference [5], SOM network learning algorithm:

1. Initialization: The connection weight \(w_{ij}\) of SOM network is assigned to the random number of \([0,1]\).
2. Provide an input mode to the input layer \(P_k\) and normalize it according to the following formula.
   \[
   \overline{P_k} = \frac{P_k}{\|P_k\|} = \frac{p_{k1}^{1}p_{k2}^{2}...p_{kn}^{n}}{\left[p_{k1}^{2}+(p_{k2}^{2})^{2}+...+(p_{kn}^{2})^{2}\right]^{1/2}}
   \] (1)
3. The connection weight vector \(w_j\) is normalized and the Euclidean distance between \(\overline{w_j}\) and \(P_k\) is calculated.
\[ W_k = \frac{w_j}{\|w_j\|} = \frac{(w_{j1}, w_{j2}, \ldots, w_{jN})}{[(w_{j1})^2 + (w_{j2})^2 + \cdots + (w_{jN})^2]^{\frac{1}{2}}} \]  

(2)

\[ d_j = \left[ \sum \frac{(P_i^k - W_j)}{2} \right]^\frac{1}{2}, j = 1, 2, \ldots, m \]  

(3)

4. The minimum distance is found to determine the winning neuron \( g \).

\[ d_g = \min \left[ d_j \right], j = 1, 2, \ldots, m \]  

(4)

5. According to the following formula, the connection weights between all neurons in the competitive layer and neurons in the input layer are adjusted.

\[ W_{ji}(t+1) = W_{ji}(t) + \vartheta(t) \times \left[ P_i^k - w_{ji}(t) \right] \]  

Where, \( j \in N_g(t), j = 1, 2, \ldots, m \), \( \vartheta(t) \) is the learning rate at time \( t \).

6. Another input mode is selected to provide to the input layer and return to step (3) until all learning modes are provided to the network.

7. Update learning rate \( \vartheta(t) \) and neighborhood \( N_g(t) \).

\[ \vartheta(t) = \vartheta(0) \left( 1 - \frac{t}{T} \right) \]  

(5)

\[ N_g(t) = NT[N_g(0) \left( 1 - \frac{t}{T} \right)] \]

8. Let \( t = t + 1 \) and return to step (2) until \( t = T \).

3. Knowledge reduction model

According to the actual data collected, a two-dimensional information table of rough set is formed by using SOM network automatic clustering algorithm, which often contains vague, unimportant and redundant attributes. Knowledge reduction means to remove redundant attributes and extract redundant attributes, to generate decision rules effectively [6].

In this paper, a rough set attribute reduction algorithm based on Discernibility Matrix (DM) [7] is proposed, to reduce the redundant knowledge in the two-dimensional decision information table of evacuation. Decision discernibility matrix is generated to solve the resolution function. Each disjunctive item in the Disjunctive Normal Form (DNF) of the resolution function corresponds to an attribute reduction, as well as a combination of conditional attributes (rule precursors) of the decision rules. There is a lot of computational redundancy in the traditional transformation from Conjunctive Matrix (CM) to Disjunctive Matrix (DM). Due to the inherent relationship between the reduced DM and the disjunctive paradigm, this paper uses the method of directly generating disjunctive terms to reduce redundant attributes.

After the CM matrix is reduced, the conditional attribute exist in the disjunctive paradigm, only when the column value (conditional attribute code) is 1. Moreover, the non-zero conditional attributes in each row are combined with the non-zero conditional attributes in the next row. In this way, non-repetitive disjunctive terms are formed. The number of disjunctive terms can be directly calculated by the sum of the number of non-zero elements in each row. It will reduce the search space and save the computing time, if only the attributes whose CM matrix element value is 1 are combined. The flow chart of the proposed knowledge reduction model is shown in Figure 1.
Figure 1. The flow chart of the proposed knowledge reduction model

Attribute reduction algorithm in the proposed knowledge reduction model is introduced as follows[8]:

1. The number of non-zero elements per row in CM matrix, i.e. the number of attributes:
   \[ \text{row}_{\sum}(i) = \sum_{j=1}^{n} CM(i,j) \]  

2. Index of subscript attribute (conditional attribute number):
   \[ \text{row}_{\text{no_zero}}(i, \text{temp}) = j, \text{if } CM(i,j) \neq 0; i = 1, \ldots, m; j = 1, \ldots n; \text{temp} = \text{temp} + 1; \]

3. The number of disjunctive terms contained in the disjunctive paradigm of the resolution function:
   \[ \text{max}_{\text{column}} = \prod_{i=1}^{m} \text{row}_{\sum}(i) \]

4. The number of columns per element in this row corresponds to the following rows:
   \[ \text{col}_{\text{per unit}} = \prod_{k=1}^{n} \text{row}_{\sum}(k) \]

5. The number of iterations of each element in the row corresponding to the disjunctive matrix:
   \[ \text{cycle}_{\text{per unit}} = \frac{\text{max}_{\text{col}}}{\text{row}_{\sum}(i) \times \text{col}_{\text{per unit}}} \]

In a row, each non-zero element is combined with the non-zero element below the row corresponding to column \( \text{col}_{\text{per unit}} \). In order to make no duplicate combinations with the elements above this line, \( \text{cycle}_{\text{per unit}} \) subcycle is also performed. The variable \( c_j \) controls the number of iterations of
elements in each row; sj determines the position of columns with non-zero elements in each row; and j determines the number of columns added to the disjunctive matrix.

\[
c_{j} = 1, \ldots, \text{cycle}_{\text{per unit}}
\]

\[
s_{j} = 1, \ldots, \text{row}_{\text{sum}(i)}
\]

\[
j = (1 + f_{\text{pos}} + \text{col}_{\text{per unit}} \times (s_{j} - 1), \ldots, (f_{\text{pos}} + \text{col}_{\text{per unit}} \times s_{j}))
\]

\[
d\text{isjuncti}o\text{on}_\text{matrix}(i,j) = \text{row}_{\text{no zero}}(i,s_{j})
\]

where the setting of variable j is important. It can be seen from formula (6) - (10) that the relationship between the ranges of variables in the mathematical model is a critical component for the expression of the whole model.

4. Case Study

There are many factors affecting the stability of crowd evacuation. In this paper, some attributes of crowd physical properties and scenario structure characteristics are selected as input of knowledge reduction model. This paper takes the Mecca stampede in 2015 as the background, and designs four different kinds of scenarios, as shown in table 2. The input variables include street length and width, crowd number and maximum crowd speed. The characteristics of four scenarios are used as input of the judgment model of crowd evacuation stability, and the decision attributes of crowd evacuation stability are obtained by rough set knowledge decision-making method.

Table 2. Simulation parameters of scenarios

| Attributes       | Scenario | Number of people(p) | Length of main street (m) | Width of main street (m) | Length of branch street (m) | Width of branch street (m) | Maximum speed of people (m/s) |
|------------------|----------|---------------------|---------------------------|--------------------------|-----------------------------|----------------------------|-------------------------------|
|                  | 1        | 15000               | 500                       | 10                       | 350                         | 8                         | 1.5                           |
|                  | 2        | 20000               | 450                       | 9                        | 300                         | 8                         | 1.3                           |
|                  | 3        | 20000               | 300                       | 8                        | 250                         | 6                         | 1.0                           |
|                  | 4        | 18000               | 300                       | 6                        | 150                         | 5                         | 0.7                           |

Table 3 gives a comparison of the data obtained from the decision-making model with knowledge reduction and the decision-making model without reduction, in which the trampling probability is obtained by questionnaire survey and expert judgement.

It can be seen that when the judgment reliability of the decision-making model based on knowledge reduction is unchanged, the decision-making time (computing time) is greatly reduced. It can be seen that the knowledge reduction model based on rough set of crowd evacuation stability proposed in this paper is feasible.

Table 3. Comparison of the data obtained from two decision-making models

| Decision attribute | Decision model | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 |
|--------------------|----------------|---|---|---|---|---|---|---|---|---|---|---|---|
| Stampede probability (%) | Unreduced decision model | 18.0 | 33.2 | 51.6 | 68.4 | 1 | 2 | 3 | 4 | 0.56 | 0.67 | 0.89 | 1.13 |
| Instability level (min) | Unreduced decision model | 18.2 | 33.1 | 51.9 | 68.6 | 1 | 2 | 3 | 4 | 0.35 | 0.45 | 0.56 | 0.67 |

5. Summary

In crowd stampede events, the evolutionary characteristics of crowd evacuation scenario features and stability state are complex and difficult to measure, so it is difficult to form effective emergency management knowledge. In this paper, the knowledge representation paradigm of rough set theory is used to define the knowledge representation category of the evolution of population stability state, and SOM self-organizing clustering network algorithm is used to discretize the continuous feature attributes to form a two-dimensional decision information table. Then, the improved knowledge reduction model of rough set based on discernibility matrix is used to reduce the redundant knowledge of the two-dimensional decision information table in rough set domain. The knowledge reduction model of crowd evacuation stability proposed in this paper achieves efficient and stable in acquisition of crowd
evacuation stability evolution knowledge, therefore, this contribution can support emergency evacuation
decision-making and prevent congestion trampling events.

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