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Knowledge Management Model for Urban Flood Emergency Response Based on Multimodal Knowledge Graphs

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Abstract: Recently, frequent flood disasters in China have seriously threatened economic development and public safety. This paper addresses the need for a dynamic urban flood emergency knowledge management system in emergency management departments and the lack of systematic knowledge among emergency managers regarding urban flood control. A multimodal knowledge graph-based urban flood emergency knowledge management model was constructed to enhance the decision-making capabilities of emergency management departments, improve the efficiency of public emergency evacuation, and reduce losses from urban flood disasters by analyzing the shortcomings of the existing emergency management system. An intelligent and dynamic flood emergency knowledge management model was built. This paper integrates multimodal knowledge graph technology to establish a multimodal emergency knowledge management framework for urban flood control. It develops and simulates the proposed model's application scenarios for urban flood emergency evacuation using the Flocking algorithm on the NetLogo platform. Through simulation experiments, the practicality and effectiveness of the model in real flood disaster situations were examined, particularly in simulating crowd evacuation behavior. The study found that the model significantly improves the accuracy of information and decision-making speed during emergency responses and supports emergency management departments in conducting targeted and personalized emergency decisions. This research provides a scientific basis for emergency management departments to optimize their emergency response strategies to flood disasters and serves as a reference and example for the application of multimodal knowledge graph technology in emergency management.

Keywords: urban flood control; multimodal data; knowledge graph; emergency response; emergency evacuation



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1. Introduction

Recently, the incidence of flood disasters in China has been increasing. In 2023, the average precipitation in China was 612.9 mm, 3.9% less than usual, and there were 35 regional heavy rain processes. A total of 52.789 million people were affected by floods, 309 people were killed and missing, 130,000 houses collapsed, and direct economic losses amounted to CNY 244.57 billion. In addition, 3666 geological disasters, such as landslides, collapses, and debris flows, occurred in China, and the disaster level was mainly trimmed [1]. With the rapid development of China's urbanization process, the central part of flood losses has been transferred from rural areas to cities, and urban flood control has become the top priority of China's emergency management [2].

The knowledge scope covered in the field of urban flood control is extensive, encompassing various aspects, such as urban hydrology, urban meteorology, urban rail transit, urban economy, and urban population distribution. Due to the complexity of obtaining urban flood control knowledge and the need for different databases to store data on various structures, the methods of data processing also vary. Therefore, urban flood control data are

categorized into structured data, semi-structured data, and unstructured data. Structured data refers to highly organized data, such as meteorological databases, geospatial databases, and population and economic statistical databases. Semi-structured data primarily refers to data in web page formats, such as government information disclosure platforms. Unstructured data include journal articles related to urban flood control, flood control books, paper records, images, videos, and other such data [3].

As the field of urban flood control involves a wide range of knowledge, problems such as the lack of timeliness of emergency decision-making and the lack of scientific emergency command often occur in the process of urban flood control and disaster reduction due to the lack of a dynamic emergency knowledge management system of emergency management departments and the lack of systematic knowledge of urban flood control and emergency managers. Data are integrated, processed, and analyzed based on a multimodal knowledge map to build a knowledge management model for urban flood prevention and emergency response, which can provide scientific and visual knowledge services for flood prevention and disaster reduction and emergency response for emergency management departments before the onset of flood and flood disasters, improve emergency decision-making and command capabilities of emergency managers, and improve emergency rescue efficiency. We will comprehensively promote the modernization and intelligentization of urban flood control emergency management systems and capabilities.

2. Multimodal Knowledge Graph

As the founder of knowledge graph technology, Google is the first company to use knowledge graph technology to optimize search engine retrieval functions. Its principle is to build a substantial semantic network, associate entities, and concepts in the objective world; effectively integrate data with the help of data mining, machine learning, deep learning, and other technologies; and discover potential entity relationships and convert them into knowledge for use. At present, many scholars at home and abroad are studying the application of knowledge graph technology in earthquake prevention and disaster reduction. Du Zhiqiang, Li Yu, and other scholars formed the conceptual framework of a knowledge graph through ontology modeling and realized the transformation of natural disaster emergency knowledge from multi-source data to interconnected knowledge [4]. Scholars such as Tao Kunwang and Zhao Yangyang pointed out the risks and challenges faced by applying knowledge graph technology in disaster prevention and control [5]. Liu et al. built knowledge maps based on ontology mapping to characterize and store complex entities and relationships among disaster-related information. Node importance analysis and community discovery algorithms are used to analyze the community structure of essential nodes, and experiments validate the typical rainstorm and flood disaster risk assessment emergency service scenario. The results show that the constructed knowledge map of natural disaster emergency services can support the formal expression of semantic associations among disaster scenarios, model methods, and disaster data [6]. Zou et al. analyzed the nature of urban rainstorm disaster events, analyzed their components and dynamic characteristics from the occurrence mechanism of urban rainstorm disaster events, and proposed a multi-level knowledge representation model consisting of event layer, object state layer, feature layer, and relationship layer. This model can express the comprehensive structure and interrelationship of urban rainstorm events and emphasize the evolution process of disaster events through a series of ordered states. Taking the Zhengzhou 720 rainstorm as an example, the practicability of the constructed knowledge map is verified [7]. Duan et al. proposed a method for constructing an urban flood vulnerability index system based on bimodal objective data fusion, used a flood vulnerability knowledge map to evaluate the flood vulnerability level in the main urban area of Zhengzhou, and proposed corresponding management strategies based on the current situation of flood vulnerability in each district [8]. Jiseong Son, Chul-Su Lim, and other scholars built the flood disaster knowledge map based on the open data set, which is used to assist, solve, and manage natural disasters [9]. Currently, most studies focus on using single-modal knowledge maps

to solve the problem of natural disasters. However, single-modal knowledge maps can only be used to deal with structured data and text data, and there are still much unstructured data, such as pictures and videos in real life, that have yet to be widely used.

Multimodal knowledge graphs build upon traditional knowledge graphs by supplementing entity categories. Multimodal knowledge graphs can mine the semantic relationships between structured data and text data and delve deeper into more modal data, such as images, videos, and audio. Many things in life exist in multiple modal forms; for example, the entity of an apple can be represented in text, images, or videos. Multimodal knowledge graphs can describe the objective world more honestly and comprehensively, better disambiguate semantics, and build more robust semantic networks. DBpedia and IMGPedia have begun researching and constructing multimodal knowledge graphs. In 2019, the Institute of Cognitive Intelligence at Southeast University built a multimodal knowledge graph, Richpedia, using multimodal data such as text and images [10]. In recent years, research on knowledge graphs has shifted from unimodal to multimodal knowledge graphs both domestically and internationally.

3. Construction of Urban Flood Control Emergency Knowledge Management Model

3.1. Knowledge Management Model for Urban Flood Emergency

As shown in Figure 1, a city flood emergency knowledge management model based on a multimodal knowledge graph is constructed through the pattern layer, data layer, and technology layer. The pattern layer establishes the conceptual framework of the city flood emergency knowledge management model through a top-down construction process [11]. The data layer, through a bottom-up construction process, analyzes, processes, and stores data from different sources and modalities to ultimately form a multimodal knowledge graph, which serves as the core data support for the knowledge management model. The technology layer provides technical support for the pattern layer through techniques such as multimodal learning and database storage.

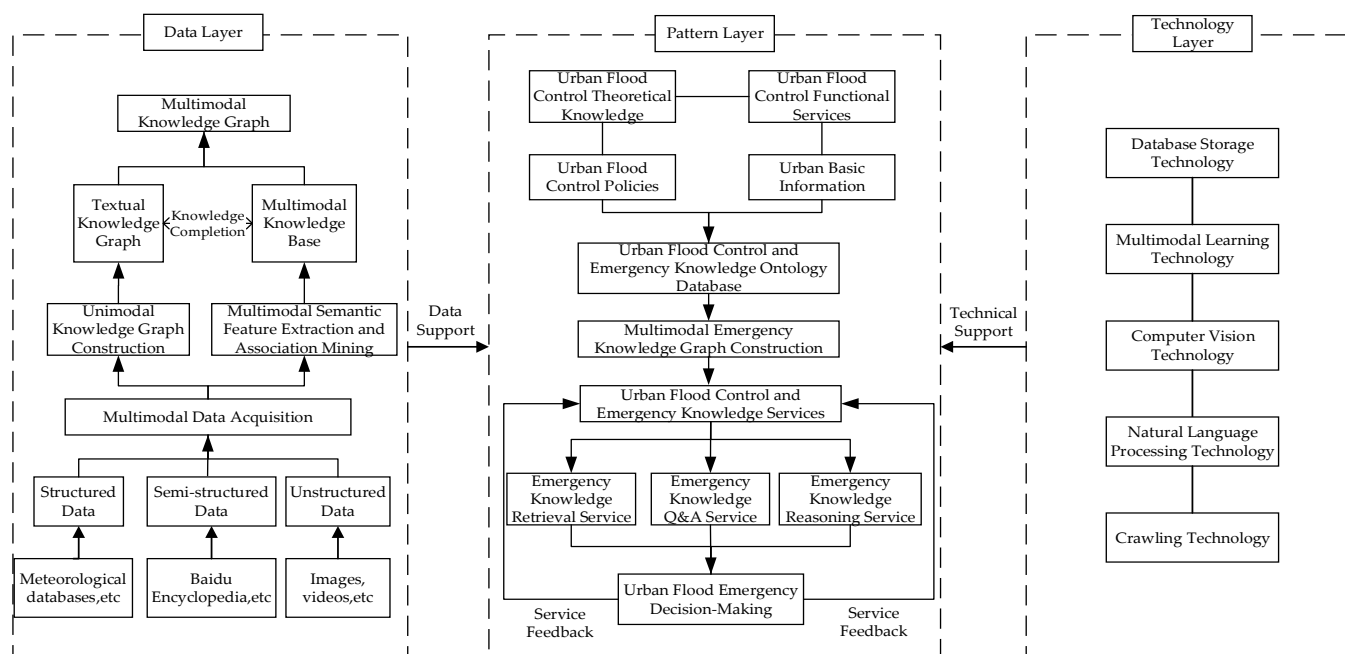


Figure 1. Knowledge management model for urban flood emergency.

3.1.1. Pattern Layer

Due to the wide range and diverse types of data sources involved in the field of urban flood control, it is necessary to first classify and summarize the relevant knowledge in the urban flood control domain and establish a city flood control knowledge ontology. This

paper takes urban flood control as the core, and builds the urban flood control conceptual hierarchy and the logical relationships between various elements around urban flood control theoretical knowledge, urban flood control policies, urban basic information, and urban flood control functional services, as shown in Figure 2.

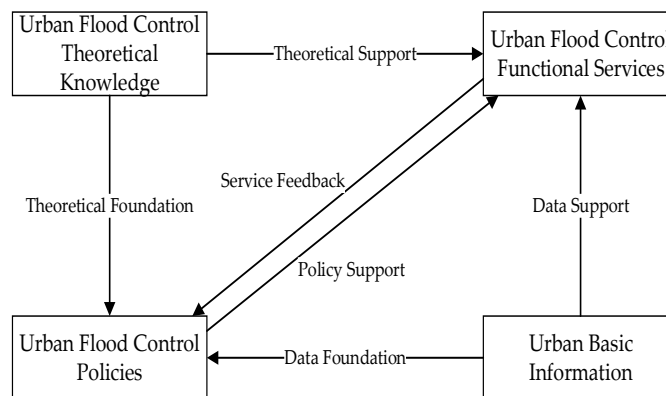


Figure 2. Logical relationships between knowledge ontologies for urban flood emergencies.

Urban flood control theoretical knowledge includes professional knowledge related to flood disasters, meteorological warnings, risk assessment models, urban flood control measures, etc., serving as the theoretical basis for providing theoretical support for urban flood control policies and urban flood control functional services. Urban flood control policies consist of national policies, laws, regulations related to urban flood disaster emergency management, urban flood control plans, strategies, etc., offering policy support for urban flood control functional services. Urban basic information comprises geographic spatial information, urban meteorological information, urban population distribution, urban economic distribution, etc., providing scientific and reliable data support for urban flood control policies and urban flood control functional services, thereby ensuring precise policy formulation and improved service implementation. Urban flood control functional services include query services for flood-related information, risk assessment services, refuge site planning services, evacuation path planning services, etc., serving as specific applications of the urban flood emergency knowledge management model and providing feedback on urban flood control policies to enhance policy formulation.

3.1.2. Data Layer

In the data layer, multimodal data are categorized based on different forms of data representation. Structured data includes meteorological databases and geographic spatial databases that provide information resources, while semi-structured data refers to data obtained from government information disclosure platforms, etc. Unstructured data refers to images, audio, 3D models, and other data obtained through sensors or the internet. The main process of building a multimodal knowledge graph in the data layer involves: (1) acquiring multimodal data from various sources; (2) using traditional knowledge graph technology to build a textual knowledge graph and simultaneously extracting semantic features and mining relationships from multimodal data; and (3) dynamically completing knowledge between the textual knowledge graph and the multimodal knowledge base. The multimodal knowledge base can provide richer multimodal entities for the textual knowledge graph, while the textual knowledge graph can supplement potential multimodal entity relationships for the multimodal knowledge base. Through dynamic knowledge completion between the textual knowledge graph and the multimodal knowledge base, deeper multimodal entity relationships are discovered. Combining expert experience with quality evaluation of urban flood control knowledge ontology, a multimodal knowledge graph is constructed.

3.1.3. Technical Layer

The technical layer includes web crawling, machine learning, deep learning, multimodal learning, and database storage technology. Web crawling technology is mainly used to acquire multimodal data. Natural language processing and computer vision technology are employed for entity recognition and semantic feature extraction of multimodal data. Multimodal learning technology establishes semantic correlations and entity alignment among multimodal data, and database storage technology stores and updates the multimodal knowledge graph.

4. Multimodal Emergency Knowledge Graph Construction

4.1. Basic Structure of Multimodal Knowledge Graph

Using the SPO triple structure, multimodal knowledge graphs describe the relationships between objective entities. The triple structure represents the relationships between entities using ‘Entity 1—Relationship—Entity 2’ for external entity relations and ‘Entity—Attribute—Attribute Value’ for internal entity relations. In this paper, we chose to construct a multimodal knowledge graph of urban flood control based on the triple structure of ‘City Flood Control Entity 1—Entity Relationship—City Flood Control Entity 2’ and ‘City Flood Control Entity—Entity Attribute—Entity Attribute Value’. Urban flood control entities include domain-specific knowledge, relevant policies, and individual urban flood protection response measures. Entity attributes further complement urban flood control entities, providing semantic descriptions through entity attribute values.

4.2. Multimodal Emergency Knowledge Graph Construction Process

The key focus in constructing a multimodal knowledge graph lies in addressing the semantic correlation between multimodal data and the integration of knowledge among multimodal entities. Firstly, due to the concatenation and heterogeneity of underlying features in multimodal data, direct correlation leads to a ‘semantic gap’ [12]. Secondly, multimodal data possess different dimensions and attributes; directly merging features from different modalities results in a ‘dimensionality disaster’ [13]. Traditional knowledge graph techniques can extract semantic and attribute relationships between entities directly through text, which is exceedingly challenging for multimodal data.

Considering the above issues, this paper constructs a multimodal knowledge graph based on multimodal deep, fine-grained semantic association technology [14]. A multimodal knowledge base is built by employing deep learning methods to extract semantic features from multimodal data, mapping the features of multimodal data to a shared semantic space, and performing association mining of multimodal data in this space. The multimodal knowledge base is supplemented with more entity relationships through the dynamic completion of knowledge from text-based knowledge graphs and the multimodal knowledge base.

4.2.1. Multimodal Semantic Feature Extraction and Association Mining

Multimodal data exhibit heterogeneity, leading to the problem of ‘semantic gap’ when interpreting the same semantics across different modalities. Since the underlying features of different modalities cannot be directly correlated, it is necessary to extract semantic features from the high-level semantics of multimodal data, map the underlying features of different modalities to a shared semantic space, and achieve semantic correlation in this shared semantic space. The approach in this paper is illustrated in Figure 3.

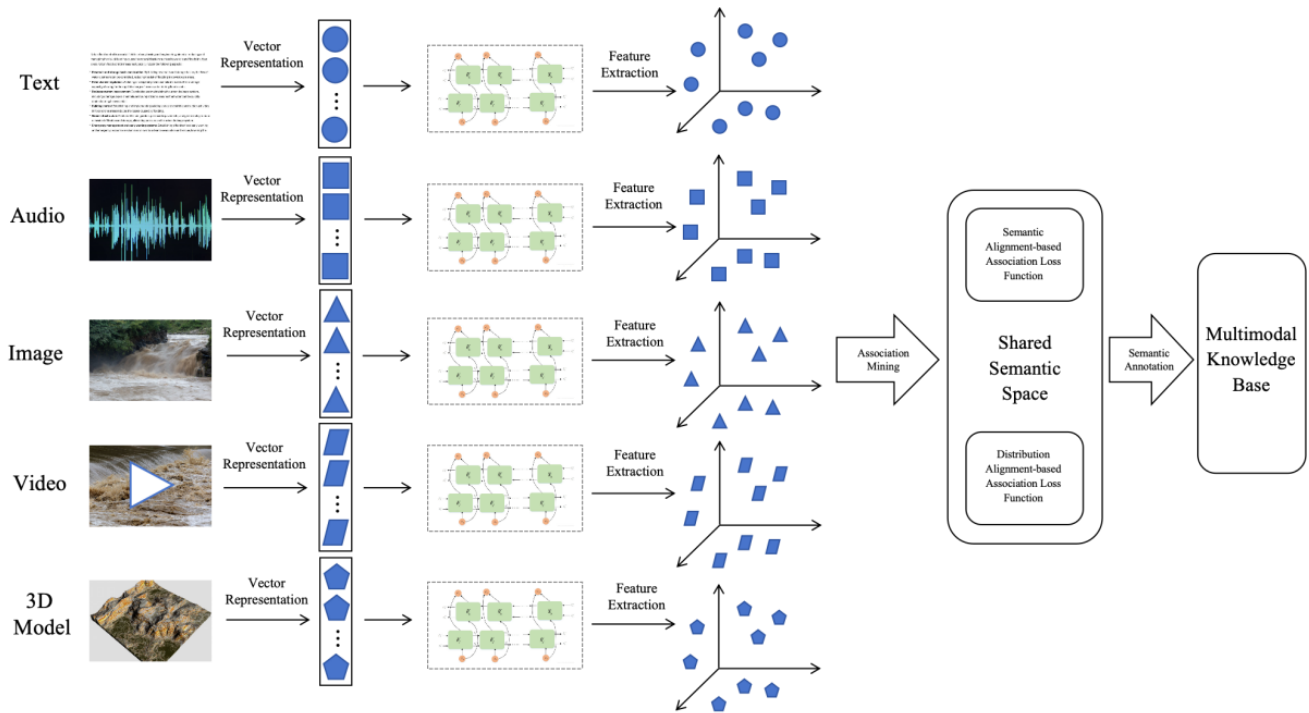


Figure 3. Flowchart of semantic feature extraction and correlation mining.

4.2.2. Multimodal Semantic Feature Extraction

This paper symbolically represents multimodal data, wherein the multimodal data set is denoted as $M = \{M^T, M^A, M^I, M^V, M^D\}$, and text, audio, image, video, and 3D model data, representing five modalities, are represented as $\{m^t, m^a, m^i, m^v, m^d\} \in M$. The data types of multimodal data are represented as $f \in \{t, a, i, v, d\}$. Through the aforementioned representation method, multimodal data and their category labels can be uniformly represented as $\{m^f, s^f\} \in M$.

When extracting the low-level features of multimodal data for text data, the text is first segmented based on sentences and paragraphs and then inputted into a convolutional neural network (CNN) [15] to extract low-level features from each segment. Data compression is performed first for image and video data, followed by input into a VGG-19 CNN [16] to extract low-level features. The audio data are segmented based on fixed time points, and Mel-frequency cepstral coefficients (MFCCs) are extracted as the low-level features for each segment. For structurally complex 3D model data, this paper uses light field descriptors [17] to comprehensively extract low-level features from various angles of the model.

The results are inputted into a Bi-LSTM [18] to learn contextual information about the underlying features by utilizing different models to vectorize the underlying features of multimodal data. Bi-LSTM, built upon the traditional recurrent neural network, is optimized to effectively address various issues encountered during gradient descent computation in the latter. Bi-LSTM consists of two LSTM units, forward and backward, where LSTM includes input gates, output gates, and forget gates, mathematically expressed as

$$\begin{Bmatrix} i_t \\ o_t \\ f_t \end{Bmatrix} = \text{sigmoid} \left(\begin{Bmatrix} W_i \\ W_o \\ W_f \end{Bmatrix} [x_t, h_{t-1}] + \begin{Bmatrix} b_i \\ b_o \\ b_f \end{Bmatrix} \right), \quad (1)$$

$$\tilde{C}_t = \tanh(W_c[x_t, h_{t-1}] + b_c), \quad (2)$$

$$C_t = C_{t-1} \times f_t + \tilde{C}_t \times i_t, \quad (3)$$

$$h_t = o_t \times \tanh(C_t), \quad (4)$$

where i represents the input gate, o represents the output gate, f represents the forget gate, and C represents the memory unit. W_i , W_o , W_f , W_c , respectively, denote the weights that the LSTM network needs to calculate, and $\tilde{C}$ represents the information retained in C . The vector sequence obtained from the output gate can further be inputted into a fully connected layer for learning, obtaining the sequence feature $h_{seq}^f = \{h_1^f, \dots, h_n^f\}$ of multimodal data. Then, the average of the sequence feature h_{seq}^f is calculated to derive $h^f = 1/j \sum_{n=1}^j h_n^f$, where j represents the total length of the sequence. Through a series of calculations, the contextual information in the underlying features of multimodal data is fully integrated, transforming coarse-grained underlying features into fine-grained semantic features, thereby providing assurance for the subsequent exploration of semantic correlation in multimodal data.

4.2.3. Multimodal Semantic Association Mining

After obtaining the semantic features of multimodal data, a unified mapping in semantic space is performed on these features to mine the potential associations at a high-level semantic level among the multimodal data. This paper implements the mining of associations at a high-level semantic level using a multimodal associative loss function based on semantic and distribution alignment.

For the multimodal alignment loss function based on semantic alignment, the semantic features of multimodal data are first inputted into a fully connected neural network (FC) for unified representation, mapping the results to a shared semantic space. The following function is used to constrain the high-level semantic alignment between multimodal data:

$$L_{SA} = l_{sm}(h^f, y^f) + l_{trip}(h^f, y_s^f, \hat{y}_s^f), \quad (5)$$

$$l_{sm}(h^f, y^f) = -\sum_{q=1}^n 1\{y^f = q\} \log[\hat{p}(h^f, q)], \quad (6)$$

$$l_{trip}(h^f, y_s^f, \hat{y}_s^f) = \max(0, \alpha + f(h^f, y_s^f) - f(h^f, \hat{y}_s^f)), \quad (7)$$

where $l_{sm}(h^f, y^f)$ represents the cross-entropy loss function and y^f is used to denote the high-level semantic label of h^f , with a total of n semantic categories. When $y^f = q$, the value of $1\{y^f = q\}$ is 1; otherwise, it is 0. $\hat{p}(h^f, q)$ represents the probability that the semantic features match the q -th high-level semantic category.

For $l_{trip}(h^f, y_s^f, \hat{y}_s^f)$, first, through the Word2Vec [19] model, feature extraction is conducted on semantic labels corresponding to all semantic categories, resulting in feature vectors $\{y_1, \dots, y_n\}$ for the semantic labels. $\hat{y}_s^f$ represents the feature vectors corresponding to the semantic features, while y_s^f represents the feature vectors that do not correspond to the semantics. The semantic features of multimodal data and semantic labels are represented through triplets. Based on high-level semantic categories, by reducing the distance between data with the same semantic category and expanding the distance between data with different semantic categories, semantic clustering of multimodal data is performed. Through a multimodal alignment loss function, the semantic recognition ability of multimodal data is improved, effectively mining semantic correlations in multimodal data.

Meanwhile, a multimodal data association loss function based on distribution alignment is designed. Firstly, the maximum mean discrepancy (MMD) loss function [20] is adopted to reduce the differences in spatial distribution between multimodal data. MMD can intuitively judge the spatial distribution differences between two datasets and is currently widely used as a loss function for optimization in transfer learning neural networks. Through the gradient descent algorithm, we find the minimum value of the MMD loss function to reduce the differences in spatial distribution between multimodal data and achieve distribution alignment. The multimodal association loss function based on distribution alignment can be expressed as

$$L_{DA} = \sum_{x,y} g_{mmd}(h^x, h^y), \quad (8)$$

where x and y represent different modal data types. The MMD loss function between the two modal data types can be expressed as

$$g_{mmd}(h^x, h^y) = ||E_X[\phi(h^x)] - E_Y[\phi(h^y)]||_{H'}^2, \quad (9)$$

where the MMD loss function is a squared representation of the reproducing kernel Hilbert space (RKHS), and through the gradient descent algorithm, finding the minimum value of the MMD loss function can achieve distribution alignment between two different modal data. In summary, the multimodal correlation loss function is represented as

$$L = L_{SA} + L_{DA}, \quad (10)$$

By minimizing the above loss function, data from different modalities are clustered around the same semantics, reducing the distribution differences between modal data and establishing semantic correlations among them. After uncovering the semantic correlations of multimodal data, semantic annotation is performed, and the annotated multimodal data are stored as high-level semantic groups in the multimodal knowledge base.

4.2.4. Multimodal Dynamic Knowledge Completion

This paper uses traditional knowledge graph technology to construct a textual knowledge graph while simultaneously building a multimodal knowledge base through multimodal semantic feature extraction and association mining techniques. Through dynamic knowledge complementation between the two, as shown in Figure 4, a multimodal knowledge graph is constructed.

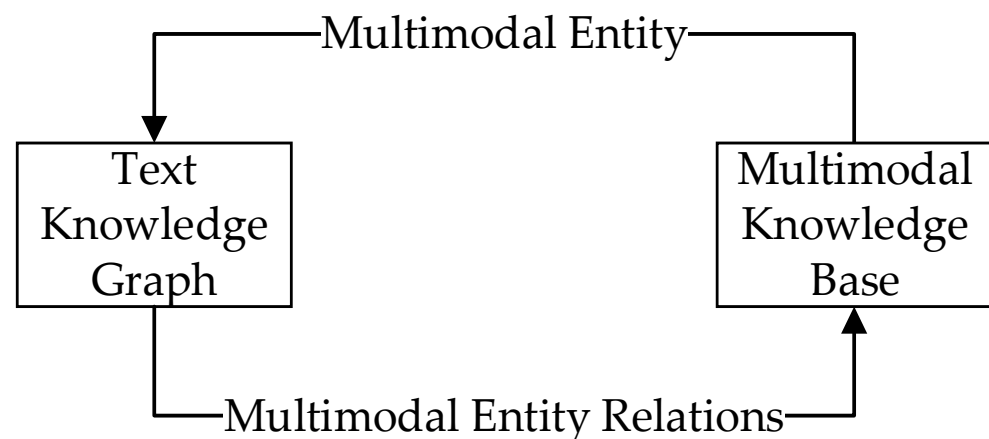


Figure 4. Dynamic knowledge completion.

The traditional knowledge graph only contains text entities that must be revised in knowledge representation, making it difficult to disambiguate semantics during entity alignment. By introducing a multimodal knowledge base, it is possible to enrich the text knowledge graph with multimodal entity completion. Through dynamic knowledge completion between the text knowledge graph and the multimodal knowledge base, the text knowledge graph can be improved while uncovering deeper semantic relationships through knowledge reasoning. Finally, by employing expert experience and an urban flood control knowledge ontology, a quality assessment can be conducted to construct a multimodal knowledge graph oriented toward urban flood control.

5. Knowledge Services for Urban Flood Emergencies

The urban flood emergency knowledge management model, with a multimodal knowledge graph at its core, extensively acquires urban flood data from different sources and modalities. After data integration, processing, and analysis, it uncovers potential semantic relationships among urban flood entities, establishing a large-scale urban flood knowledge

network. Through knowledge retrieval, knowledge question-answering, and knowledge reasoning services, this model can meet the needs of users at different levels and from different groups, providing emergency management departments with diversified, personalized, and intelligent emergency knowledge services.

5.1. Emergency Knowledge Retrieval Service

The vast amount of urban flood prevention knowledge resources has increased users' difficulty accessing them. To better meet user needs, the urban flood emergency knowledge management model provides users with convenient knowledge retrieval services. This model is based on ontology-based knowledge retrieval technology [21]. After users input keywords, it extracts entities from the urban flood emergency knowledge ontology database. It matches the semantic similarity between entities in the multimodal emergency knowledge graph, presenting the highest similarity results to users. The output results include text data and rich multimodal data, such as audio, images, and videos, providing users with diversified and visualized urban flood emergency knowledge.

5.2. Emergency Quiz Service

The urban flood emergency knowledge management model provides users with intelligent knowledge question-answering services. This model uses knowledge graph embedding for knowledge question-answering methods [22]. After users input a question, the model converts the natural language question statement into a structured representation of the "head entity—relationship—tail entity" triplet. It extracts the predicted head entity from the urban flood emergency knowledge ontology database, analyzes the predicted relationship using deep learning methods, and searches for a highly similar predicted tail entity in the multimodal emergency knowledge graph, presenting the tail entity with the highest score as the answer to the user.

5.3. Emergency Knowledge Reasoning Service

The urban flood disaster reduction process contains a wealth of explicit knowledge that can be directly conveyed through language, text, and other means, as well as a good deal of implicit knowledge that people cannot directly discover and express. The urban flood emergency knowledge management model is based on knowledge reasoning methods from multimodal knowledge graphs. Analyzing the underlying features of different modal data explores the potential semantic associations between urban flood entities. It continuously engages in knowledge analysis, reasoning, and innovation cyclically to unearth more potential implicit knowledge. This model aims to provide users with extensive and comprehensive emergency knowledge reasoning services.

The knowledge services provided by the urban flood emergency knowledge management model allow emergency management departments to effectively respond to floods and waterlogging disasters of varying degrees and scales. This allows for more refined, personalized, and intelligent emergency decision-making tailored to different regions and cities, considering population distribution and economic conditions. Additionally, the model provides feedback on the outcomes of these decisions, enabling the optimization of knowledge services and establishing a dynamic urban flood emergency knowledge management system.

6. Simulation Study of Urban Flood Emergency Evacuation Based on ABM

When flood disasters occur, orderly evacuation of large-scale crowds is crucial for reducing the risk associated with these disasters. This article explores the potential impact of the urban flood control emergency knowledge management model on residents' performance in disaster response. For this purpose, this study utilizes the principles of the Flocking algorithm. It constructs a flood disaster emergency evacuation simulation model on the NetLogo platform, which can simulate the escape behavior of crowds during flood disasters.

The simulation environment described below divides the population into two types: blind people and knowledgeable people. Blind people lack extensive knowledge about flood emergency evacuation and cannot accurately grasp real-time flood situations, whereas knowledgeable individuals possess this information. The model's input parameters primarily include fixed and variable parameters, where fixed parameters, such as minimum separation and max-align-turn, are mainly used to optimize the visualization of the model's outputs, enabling a clearer understanding of the model's performance. Variable parameters such as population represent the number of people evacuating, water depth indicates the water depth, and percentage represents the proportion of knowledgeable individuals within the crowd. The horizontal axis represents the time step of the model or the number of iterations—that is, the discrete time unit in the simulation process. Each time step corresponds to a complete iteration of the model. This division of time steps is helpful in observing and analyzing the change trend of crowd evacuation behavior over time. The vertical axis represents the model's output variable right movers, that is, the number of individuals who choose the correct route to escape in each time step or number of iterations, reflecting the number of individuals who successfully follow the preset safe route to escape in the simulated flood disaster emergency evacuation process, which is an important indicator for evaluating the effectiveness of evacuation strategy and crowd behavioral response.

Initially, blind individuals move in random directions, tending to approach nearby individuals and move in the same direction as those nearby; when they get too close, they take measures to increase the distance between each other. Meanwhile, knowledgeable individuals use a dynamic warning system based on the knowledge management model to obtain real-time information on flooding, enabling them to have clear paths to safe areas. In the simulated flood disaster street scenario, safe areas and flood-affected areas are randomly set, with preset flooded areas on the streets (although water depth affects individuals' movement speed, it does not interfere with the decision-making process of blind or knowledge-driven individuals).

6.1. Crowd Evacuation Behavior in the State of Nature

In an environment lacking guidance from a knowledge management model, individuals cannot accurately obtain specific flood information on the roads and exhibit a pattern of blind following behavior. This behavior becomes more pronounced when a large crowd is trapped in a street scene affected by flooding. At this point, the group tends to move collectively in a specific direction. The green area in the figure below represents the total number of individuals moving towards safe areas, as shown in Figure 5. In evacuation scenarios without guidance from a knowledge management model, the blind following behavior among individuals tends to align, leading the group towards a potential danger zone. In such situations, the survival probability of the group is significantly uncertain. As shown in Figure 5a, even if some individuals initially choose the correct escape route, others may follow the opposite direction that the majority chooses, thereby abandoning the potentially correct choice that is not yet entirely certain psychologically.

At the same time, when the number of groups gradually increases, making the area too densely populated, each blind follower will be influenced by multiple other individuals at the same time, resulting in the inability to form a consistent direction of travel, as shown in Figure 5c. In this scenario, the number of individuals choosing to move in a safe direction will be only half of the total population. In contrast, the remaining individuals will move in a potentially dangerous direction.

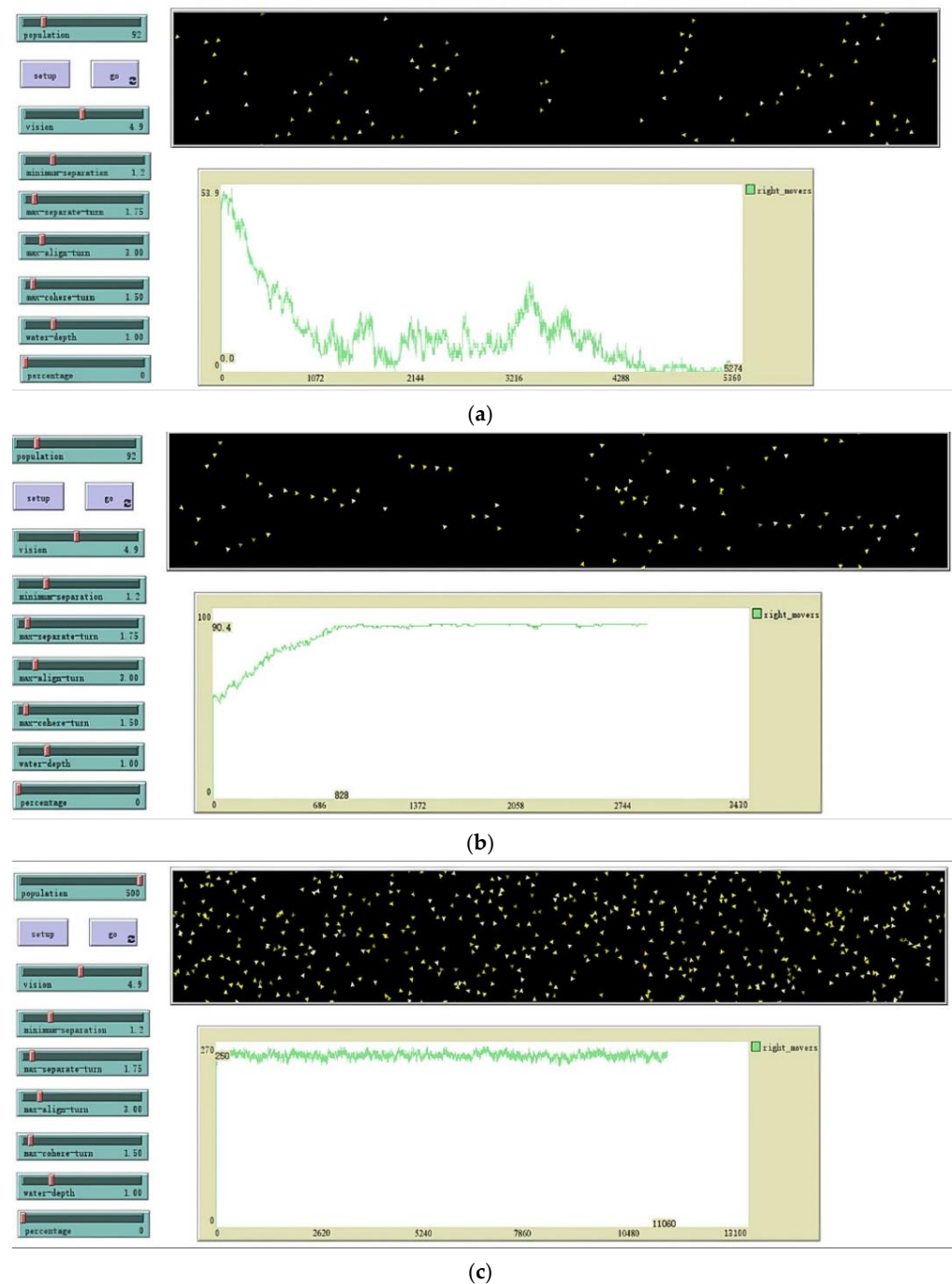


Figure 5. Evacuation diagram in the natural state. (a) Natural evacuation conditions. (b) The evacuation of a large number of people in a natural state. (c) Introduce the evacuation of knowledge.

6.2. Crowd Evacuation Behavior Guided by Knowledge Management Model

According to the simulation analysis of flood disaster evacuation in Figure 6a–c, it is evident that the introduction of knowledgeable individuals into the affected population at proportions of 10%, 25%, and 50% of the total affected population effectively promotes the evacuation of the affected population to safe locations. Furthermore, the study found that as the proportion of knowledgeable individuals increases, the speed at which the affected population converges toward safe locations significantly accelerates. When the proportion of knowledgeable individuals is 10%, the affected population requires approximately 820 time units to achieve unified, safe evacuation. However, when the proportion of knowledgeable individuals increases to 25% of the total population, the required time

decreases to 578 time units. When the proportion increases to 50%, the required time further reduces to 429 time units, representing a 47.7% reduction in evacuation time compared to the scenario with a 10% proportion, greatly enhancing the emergency evacuation efficiency of the affected population.

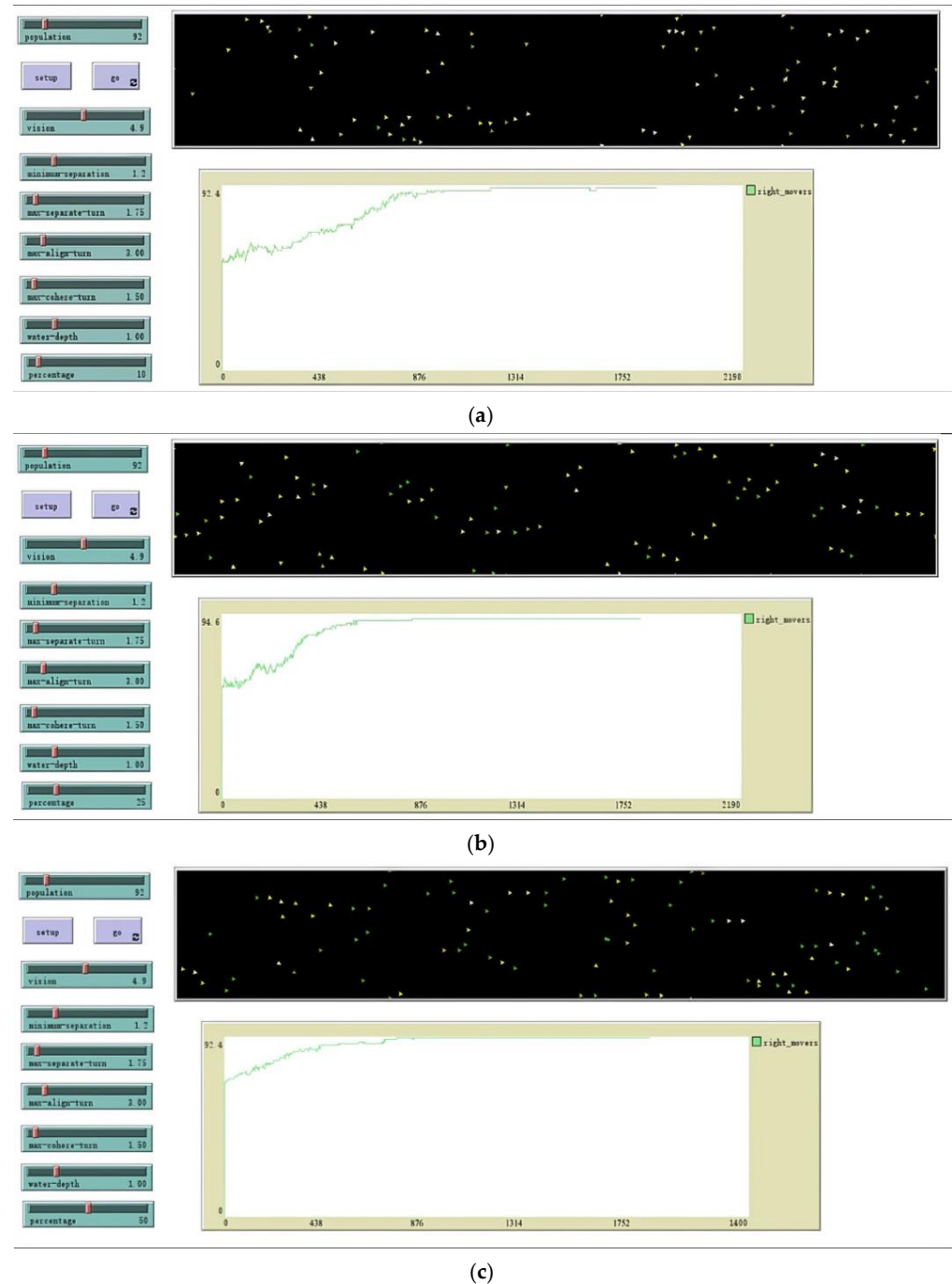


Figure 6. Evacuation diagram guided by the knowledge management model. (a) Knowledgeable individuals into the affected population at proportions of 10%. (b) Knowledgeable individuals into the affected population at proportions of 25%. (c) Knowledgeable individuals into the affected population at proportions of 50%.

This series of comparative analyses indicates that in the disaster response process, even a relatively small proportion (10%) of knowledgeable individuals can induce blind people to move toward safe locations through the herd effect. With the continuous in-

crease in the proportion of knowledgeable individuals, this guiding effect becomes more significant, enabling faster emergency evacuation of the population. Therefore, this study highlights the importance of having a comprehensive, efficient, and accurate multimodal knowledge management model in flood disaster emergency management. The knowledge management model not only accelerates the safe evacuation process of the population but also significantly enhances the overall efficiency of disaster response measures, thereby reducing potential casualties and property losses. Furthermore, this finding provides crucial strategic guidance for disaster emergency management, emphasizing the critical role of knowledge dissemination and application in disaster response.

7. Extended Application Scenarios of Urban Flood Emergency Knowledge Management Model

The urban flood emergency knowledge management model based on a multimodal knowledge graph integrates data from various sources and modalities in urban flood control to acquire, consolidate, analyze, and reason. It can provide scientific and visualized support for emergency management of urban flooding disasters. Taking urban flood prevention in Beijing as an example [23], this paper analyzes the current pain points in urban flood control in Beijing. It proposes corresponding solutions based on the urban flood emergency knowledge management model to promote the construction of Beijing as a sponge city.

After summarizing, the current pain points in urban flood control in Beijing are identified as follows: (1) the “four anticipations” system (forecast, alert, rehearsal, and plan) of urban flood control in Beijing needs further improvement; (2) the intelligent management system for urban drainage in Beijing needs to be strengthened; (3) the flood control knowledge and skills of Beijing residents need further enhancement. Based on these issues, this paper proposes the following four application scenarios based on the urban flood emergency knowledge management model:

7.1. Urban Flood ‘Four Anticipations’ System Based on Emergency Knowledge Management Model

The ‘four anticipations’ system of urban flood control includes forecasting, alerting, rehearsing, and planning. Beijing has already established a ‘four anticipations’ system for urban flood control, which can preliminarily forecast the range of torrential rain, warn of the risk levels of internal flooding, rehearse flood rescue and disaster relief, and plan for flood emergency management. After introducing the urban flood emergency knowledge management model by integrating multimodal data such as radar maps, remote sensing images, and satellite cloud images, it provides meteorological forecasters with visual knowledge, refines the standards for forecasting torrential rains, and strengthens the capability to respond to rainstorm alerts. Integrating multimodal knowledge in the field of urban flood control promotes the intelligentization of urban flood drills and the scientific formulation of flood contingency plans.

7.2. Intelligent Urban Drainage Management Based on Emergency Knowledge Management Model

Currently, the data on urban drainage networks in Beijing are scattered and vague, and they are from multiple sources. The urban drainage system can be managed precisely by integrating dispersed network data. Using sensors to monitor urban drainage channels and rivers, the urban flood emergency knowledge management model based on a multimodal knowledge graph integrates the multimodal data obtained from monitoring, establishing an intelligent management and maintenance system for flood prevention facilities in Beijing, fully utilizing the regulatory and beneficial effects of Beijing’s flood prevention facilities on rainwater.

7.3. Urban Flood Knowledge Popularization Based on Emergency Knowledge Management Model

Traditional knowledge graph technology can only retrieve knowledge via keywords. With the introduction of a multimodal knowledge graph, it is possible to retrieve data across

modalities, significantly improving retrieval efficiency. Based on the emergency knowledge management model, an urban flood knowledge retrieval system is established, visualizing knowledge in the field of flood disasters for emergency management decision makers and citizens. This system not only enhances the scientific decision-making ability of managers but also popularizes knowledge to the public, improving their scientific understanding of flood disasters and enhancing their self-rescue capabilities during urban flooding, thus enhancing the efficiency of urban flood disaster emergency management.

7.4. Social Media and Public Sentiment Monitoring Based on Emergency Knowledge Management Model

Public sentiment monitoring is integral to the entire process of emergency management. Timely and effective monitoring of public sentiment during urban flood disaster events can significantly reduce the losses caused by public sentiment incidents, prevent the spread of negative emotions, and soothe public sentiment. Traditional natural language processing technology based on text data from social media conducts sentiment analysis, but the semantic ambiguity of text data can complicate public sentiment monitoring. Moreover, the wide-ranging data sources of social media make it difficult to judge the authenticity of public sentiment events. By introducing an urban flood emergency knowledge management model based on a multimodal knowledge graph, it integrates text, images, and video data from social media, disambiguates semantics through various modal data, and integrates knowledge to judge the authenticity of public sentiment events more scientifically and effectively on social media, achieving dynamic monitoring of public sentiment in urban flood disaster events on social media.

8. Conclusions

We propose an innovative urban flood emergency knowledge management model, which is built on the basis of a multimodal knowledge map, and uses multimodal semantic association technology to extract and mine data features, so as to build a dynamic urban flood emergency knowledge map. In order to verify the key role of the model in emergency response, this study adopted the Flocking algorithm to simulate the emergency evacuation behavior during flood disasters and demonstrated the potential of the model in improving the emergency evacuation efficiency through the simulation results. This model provides not only a new technical tool for urban flood emergency management but also a new perspective on how to use multimodal data to optimize emergency decision-making. With the continuous development of multimodal learning technology, this model is expected to be further improved to provide more reliable decision support for urban flood control. Looking ahead, we expect this knowledge graph-based multimodal transport approach to be adopted globally, helping more cities improve their ability to cope with flood disasters and achieving major breakthroughs in areas such as smart city construction and urban disaster risk emergency management.

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