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Natural Disasters Warning for Enterprises Through Fuzzy Keywords Search

Zewei Sun, Hanwen Liu, Chao Yan, and Ran An*

Abstract: With the ever-increasing number of natural disasters warning documents in document databases, the document database is becoming an economic and efficient way for enterprise staffs to learn and understand the contents of the natural disasters warning through searching for necessary text documents. Generally, the document database can recommend a mass of documents to the enterprise staffs through analyzing the enterprise staff’s precisely typed keywords. In fact, these recommended documents place a heavy burden on the enterprise staffs to learn and select as the enterprise staffs have little background knowledge about the contents of the natural disasters warning. Thus, the enterprise staffs fail to retrieve and select appropriate documents to achieve their desired goals. Considering the above drawbacks, in this paper, we propose a fuzzy keywords-driven Natural Disasters Warning Documents retrieval approach (named NDWD\textsubscript{keyword}). Through the text description mining of documents and the fuzzy keywords searching technology, the retrieval approach can precisely capture the enterprise staffs’ target requirements and then return necessary documents to the enterprise staffs. Finally, a case study is run to explain our retrieval approach step by step and demonstrate the effectiveness and feasibility of our proposal.

Key words: Natural Disasters Warning Documents (NDWD); fuzzy keywords search; text description mining

1 Introduction

In recent years, destructive natural disasters (e.g., earthquake, landslides, tsunami, forest fire, and hurricane) have caused serious damages on human lives and property, especially, with the social construction and economic development of every country\textsuperscript{[1–5]}. For example, 5.12 Wenchuan earthquake\textsuperscript{[6]} in 2008 in China and devastating earthquake in 2011 in Japan have leaded serious damages to many enterprises in the economic development. In fact, the destructive natural disasters are the natural processes that take place in the ecosystem, so the occurrences of the destructive natural disasters are not in our control in many cases.

Currently, confronted with the occurrences of the destructive natural disasters, every country and the governments of all levels have proposed a variety of prevention tactics to quickly and accurately respond to the social and economic losses caused by all kinds of destructive natural disasters. Fortunately, the various prevention strategies that depict how to reduce the effect of the destructive natural disasters are all recorded at the disparate natural disasters warning documents. Thus, for the governments and enterprises, these natural disasters warning documents that depict the various prevention strategies can effectively offer scientific basis for disaster...
prevention and relief; furthermore, the governments and the enterprises can effectively increase the capabilities of disaster emergency rescue and build emergency disaster prevention support systems.

However, recent researches show that enterprise staffs will face the following several challenges to retrieve and find the satisfactory natural disasters warning documents:

1. In the retrieval process of the natural disasters warning documents, the process requires that the enterprise staffs firstly offers several keywords that describe disaster prevention and relief to document databases, and then the document databases return required documents to the enterprise staffs. In fact, the enterprise staffs fail to acquire the satisfactory natural disasters warning documents as they have little background knowledge about the natural disasters warning.

2. Furthermore, the existing keywords search approaches\cite{7,8} usually employ exact keywords-searching techniques for the natural disasters warning documents retrieval, while neglecting the synonymy and word inflections. Therefore, the enterprise staffs will be unable to obtain the desired and high-quality natural disasters warning documents.

Considering the above drawbacks, we propose a fuzzy keywords-driven Natural Disasters Warning Documents retrieval approach (named NDWD\textsubscript{keyword}). The retrieval approach allows enterprise staffs to type simple and flexible text documents (i.e., text description) instead of several rigid and professional words. Thus, the NDWD\textsubscript{keyword} lightens the enterprise staffs’ burden to search and select, and the approach effectively returns the desired and high-quality natural disasters warning documents to the enterprise staffs. Overall, our contributions in the paper are three-fold:

- We generalize enterprise staffs’ inputs from exact keywords to more comprehensive and flexible text documents describing the natural disasters warning (i.e., text description). Thus, we propose keywords-driven NDWD\textsubscript{keyword}.

- To return the desired and high-quality natural disasters warning documents, we consider the synonymy and word inflections existed in the text documents describing the natural disasters warning.

- At last, we evaluate the effectiveness and feasibility of our proposal by using a case study.

The rest of the paper is organized as follows. Related work is presented in Section 2. We introduce the research motivation in Section 3. The details of the proposed NDWD\textsubscript{keyword} approach are described in Section 4. A case study demonstrating the effectiveness and feasibility of the proposed retrieval approach is presented in Section 5. Finally, we summarize the paper in Section 6.

2 Related Work

In the past decade, economic losses resulting from natural disasters have reached trillion dollars, so the prevention strategies of the natural disasters have recently received much attention from the governments, the enterprises, and researchers.

Currently, the research on prevention strategies has been given great attention. The work of Ref. \cite{6} denoted the Emergency Decision Making (EDM) for natural disasters, exhibited three different characteristics. The main characteristic is that it should be attached to humanism, i.e., the purpose is to minimize the loss of life\cite{9} and protect property of occupants and enterprises. Meanwhile, the work of Ref. \cite{10} determined a basic architecture of an Early Warning System (EWS) for flash floods in urban areas, and the system mainly contained four structures, i.e., disaster risk knowledge, forecasting, information dissemination and communication, as well as preparedness and response. The EWS could offer an effectively prevention strategy to enterprise staffs in reducing property losses of enterprises. Furthermore, van Khoa and Takayama\cite{11} designed a Wireless Sensor Network (WSN) to monitor landslide disasters based on the EWS; the WSN could offer an effectively prevention strategy to enterprise in remote areas. After learning of the existence of natural disaster, the real-time information had a significant function for the governments and enterprises. Rudra et al.\cite{12} proposed a classification summary framework to predict how various concepts evolve on Twitter during a natural disaster. Facing to all kinds of the destructive natural disasters\cite{13,14}, enterprise staffs can reduce economic losses\cite{15} of enterprises by learning and utilizing the existing natural disasters warning documents.

To quickly search the desired natural disasters warning documents for enterprise staffs, we propose NDWD\textsubscript{keyword}. Furthermore, the retrieved documents can quickly assist enterprise staffs to learn the contents of the natural disasters warning and protect enterprises’ benefits.
3 Research Motivation

In this section, we use example of Fig. 1 to demonstrate the research motivation. Figure 1 shows that an enterprise staff needs to retrieve the following keywords to obtain the necessary natural disasters warning documents for learning and understanding the contents of the natural disasters warning: (1) "earthquake" for earthquake disaster warning research[16]; (2) "tsunami" for the tsunami disaster warning research[17]; (3) "landslide" for landslide disaster warning research[18]; and (4) "storm" for storm disaster warning research. The enterprise staffs use these four keywords in searching for the relevant natural disaster warning documents.

In the retrieval process of the natural disasters warning documents, as the enterprise staff is not an expert in the disaster prevention and relief, providing four appropriate retrieval keywords (i.e., earthquake, tsunami, landslide, and storm) is a tough one. Furthermore, the exact keywords searching technique may neglect high-quality text documents that describe natural disasters warning. For example, the text documents describing the cloudburst disaster warning would not appear in the retrieval list even if "cloudburst" and "storm" are a pair of synonyms. In view of the aforementioned analyses, NDWD<sub>keyword</sub> is necessary to improve current text documents searching way, which is introduced in detail in Section 4.

4 Natural Disasters Warning Documents Retrieval Solution

According to the analysis of the research motivation, we propose NDWD<sub>keyword</sub>. As shown in Fig. 2, NDWD<sub>keyword</sub> mainly includes the following two steps: First, we analyze the enterprise staff’s input phrases, sentences, or paragraphs that describe the contents of the natural disasters warning and convert these phrases, sentences, or paragraphs into vectors; Then, we obtain a set of candidate text documents describing the contents of the natural disasters warning by using keyword similarity calculation and optimal keyword selection. In the rest of this section, we will present the details of these two steps, separately.

Step 1: Converting enterprise staffs’ query inputs to vectors.

To facilitate the retrieval of the natural disasters warning documents, an enterprise staff can type a text description constituted by a set of phrases, sentences, even paragraphs as the enterprise staff’s query inputs. To better understand the enterprise staff’s query requirements, we must analyze and mine the text description, and then convert each text phrase, sentence, or paragraph of the text description into a vector by using natural language processing techniques.

In Step 1, we employ a word embedding tool (i.e., fastText[19]) to convert the enterprise staffs’ query inputs (i.e., text description) to vectors. Actually, the fastText is an improved version of the traditional text analysis tool Word2Vec, and the word embedding tool is developed by Facebook. Furthermore, the biggest advantage of the fastText does not rely on complex parameter tunings to make quick and accurate text classifications. Here, we assume that one text description covers l phrases, sentences, or paragraphs, and we will obtain l vectors, ω<sub>1</sub>, ..., ω<sub>l</sub>, after Step 1.

Step 2: Natural disasters warning documents searching by using keyword similarity calculation and optimal keyword selection.

In the document database, each natural disaster warning document contains multiple keywords with varied content, these keywords denote the various prevention strategies that depict how to reduce the effect of the destructive natural disasters in the economic development. Here, we employ a set S = {k<sub>1</sub>, ..., k<sub>m</sub>} to indicate the keywords of all the natural disasters warning documents. And we use the fastText of Step 1 to convert each keyword of S into an n-dimensional vector.
Next, we search for the target natural disasters warning document whose keyword $k_i$ ($k_i \in S$) achieves certain prevention strategies of the enterprise staff, according to the following keyword similarity calculation and optimal keyword selection.

Concretely, each required vector $\omega_i$ ($1 \leq i \leq l$) is firstly obtained from Step 1; Then, we search the most similar keywords (i.e., optimal keywords selection) in the natural disasters warning documents for the enterprise staff according to the keyword similarity calculation. Equations (1) and (2) are shown as follows:

$$\text{sim}_{ji} = \cos(k_j, \omega_i) = \frac{k_j \cdot \omega_i}{|k_j| \times |\omega_i|}$$  \hspace{1cm} (1)

$$k_{\text{opt}(i)} = \{k_j | \text{sim}_{ji} = \text{TOP(sim}_{ji}), 1 \leq j \leq m\}$$  \hspace{1cm} (2)

where $\text{sim}_{ji}$ denotes the similarity between $k_j$ and $\omega_i$, which is calculated by the cosine similarity ($\cos(k_j, \omega_i) \in [0, 1]$). $k_{\text{opt}(i)}$ denotes that the keyword of natural disasters warning documents which has the most similarity with the enterprise staff’s query inputs (i.e., text description $\omega_i$). Next, we traverse $S = \{k_1, \ldots, k_m\}$ and see $k_{\text{opt}(i)}$ as the optimal natural disasters warning documents’ keyword that can satisfy the enterprise staff’s learning prevention strategies. Furthermore, a new set $DK$ is used to present all the requested keywords by the enterprise staff, i.e., $DK = \{k_{\text{opt}(1)}, \ldots, k_{\text{opt}(l)}\}$. Finally, all the required natural disasters warning documents with keyword $k_{\text{opt}(i)} \in DK$ are recorded in a new set $D_1$. More details can be found in Algorithm 1.

### 5 A Case Study

In this section, a case study is discussed to demonstrate the process of the natural disasters warning documents retrieval solution.

In Fig. 3, an enterprise staff regards three phrases or sentences as the query inputs, i.e., the prevention strategies of earthquake, tsunami and storm, and the prevention strategies of landslide. Here, we use the fastText of Step 1 to transform these three phrases or sentences into vectors $\omega_1$, $\omega_2$, and $\omega_3$, respectively. As shown in Figs. 4–6, we use a set $S = \{k_1, k_2, k_3, k_4, k_5, k_6\}$ to indicate the keywords of all the natural disasters warning documents, i.e., $\{d_1, d_2, d_3\}$.

In Step 2, we firstly use Eq. (1) to execute the keyword similarity calculation,

$$\text{sim}_{11} = \cos(k_1, \omega_1) = \frac{k_1 \cdot \omega_1}{|k_1| \times |\omega_1|} = 1,$$

Next, we search for the target natural disasters warning document whose keyword $k_i$ ($k_i \in S$) achieves certain prevention strategies of the enterprise staff, according to the following keyword similarity calculation and optimal keyword selection.

Concretely, each required vector $\omega_i$ ($1 \leq i \leq l$) is firstly obtained from Step 1; Then, we search the most similar keywords (i.e., optimal keywords selection) in the natural disasters warning documents for the enterprise staff according to the keyword similarity calculation. Equations (1) and (2) are shown as follows:

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In Step 2, we firstly use Eq. (1) to execute the keyword similarity calculation,

$$\text{sim}_{11} = \cos(k_1, \omega_1) = \frac{k_1 \cdot \omega_1}{|k_1| \times |\omega_1|} = 1,$$
Next, we use Eq. (2) to execute the optimal keyword selection of Step 2,
\[ k_{\text{opt}(1)} = \{k_1| \text{sim}_1 = \text{TOP}(\text{sim}_1 = 1)\}, \]
\[ k_{\text{opt}(2)} = \{k_2| \text{sim}_2 = \text{TOP}(\text{sim}_2 = 1)\}, \]
\[ k_{\text{opt}(3)} = \{k_3| \text{sim}_3 = \text{TOP}(\text{sim}_3 = 1)\}. \]

According to \( \{k_1, k_2, k_3\} \), the natural disasters warning document \( d_1 \) contains keywords \( k_1, k_2, \) and \( k_3 \), the natural disasters warning document \( d_2 \) contains keywords \( k_1 \) and \( k_2 \). Thus, we can conclude that \( D_1 = \{d_1, d_2\}, D_2 = \{d_1, d_2\}, \) and \( D_3 = \{d_1\} \). Finally, the natural disasters warning documents \( d_1 \) and \( d_2 \) can fulfill retrieval in \( \{k_1, k_2, k_3\} \) requested by the enterprise staff, so the natural disasters warning documents \( d_1 \) and \( d_2 \) are regarded as target retrieval documents for the enterprise staff.

6 Conclusion

Early warning plays a key role in people’s daily behavior activities\(^{[20–22]} \). The reuse of natural disasters warning documents can provide the effective prevention strategies of natural disasters for enterprise staffs to further reduce the economic losses of enterprise. As existing keywords-driven documents search approach only relies on exact keywords-matching technique for the natural disasters warning documents retrieval, the recommended documents can place a heavy burden on the enterprise staffs to select and learn, especially when the enterprise staffs have little background knowledge of the contents of the natural disasters warning. Considering the above drawbacks, the paper proposes a fuzzy keywords-driven natural disasters warning documents retrieval approach, i.e., NDWD\_keyword. In NDWD\_keyword, enterprise staffs can type a set of text descriptions that contain phrases, sentences, or paragraphs to search for the desired and high-quality natural disasters warning documents. In fact, the enterprise staffs’ selection and learning burden can be lightened significantly through NDWD\_keyword. Finally, the effectiveness and feasibility of the NDWD\_keyword approach are proved by a case study.

In the following work, we will design and execute a set of experiments to further validate the effectiveness and feasibility of NDWD\_keyword approach. In addition, we will consider the privacy-preservation\(^{[23–27]} \) problems in the future research as the retrieval documents process may reveal the government’s and enterprise’s sensitive information. Moreover, diversity is often a key criterion to evaluate the performances of various decision-making systems\(^{[28–31]} \). Therefore, we will continue to refine our work to include diverse resolutions when a disaster warning occurs.

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