An edge-computing-based sensing system for geo-structure risks

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Abstract. With the advancement of geo-structures (including tunnels and underground space projects), risk management strategy has been developing rapidly in China since the 1990s. Its current practice, however, mainly focuses on the assessment of structures with qualitative or quantitative method. Currently, less attention is paid to risk control, which results in the lagged response to risk events. In this paper, risk management strategy of geo-structures at operation stage is discussed. Furthermore, an edge-computing-based risk sensing system, mainly based on image recognition, consisting of a set of cameras, edge gateways and wireless network, is proposed. The system offers real-time monitoring for structural and operational performance, and edge computing to sense early risks within geo-structures. A preliminary test of the system has been conducted.

1. Introduction
As a mega city with over 24 million populations, 100 million sq. meter of underground space, 705 km of subway with 413 stations, and 16 roadway tunnels, Shanghai is facing great challenges in safety management. Risks of geo-structures cannot be ignored.

It is commonly accepted that there are no risk-free structures. Risks of geo-structures can be managed, minimized, shared, transferred or accepted, but it cannot be ignored [1]. Therefore, great attentions should be paid to a rational risk management approach during the life-time of geo-structure, especially at operation stage. Many researches have been conducted under the topic of risk assessment qualitatively or quantitatively. If a risk event is sensed quickly and interpreted easily, economic and human lost could be avoided. In recent years, cameras combining with deep learning algorithm and ZigBee networks are popular in civil engineering for a variety of applications [2][3][4]. As the technology is evolved, cameras equipped with deep learning algorithm become more integrated, reliable and less time-consuming in data transmission, which is ideal for its combination with ZigBee.

In view of this, the paper aims to present an integrated system to monitor the risks dynamically. This paper presents an edge-computing-based risk sensing system based on deep learning, consisting of a set of cameras and edge gateways. To reach this goal, an introduction to the current practice of risk management and its limitations is presented firstly. Then, the system for monitoring the risks of geo-structures, focusing on fire events, is proposed. Signs of early fire can be captured in real time by camera and the risks could be reported simultaneously. Finally, the abovementioned system is tested effective to the fire risk control.

2. Risk management of geo-structures at operation stage
Conventional techniques to assess the condition of geo-structures at operation stage typically involve visual inspection by trained inspectors, combined with relevant decision-making criteria [5]. However, such inspection can be time-consuming, laborious, expensive, and/or dangerous.

To prevent unwanted outcomes and to mitigate their consequences to an acceptable level, the concept of risk management is introduced. A systematic risk management of geo-structures includes the procedures of system definition, risk identification, risk consequences (or probability) analysis, critical risk scenarios identification and sensitivities analysis, risk assessment and risk control [6]. Each procedure is carried out in sequence.

2.1. Current risk management of geo-structures

2.1.1. System definition. In this part, the risk management at operation stage of geo-structures is discussed, with focus on tunnels.

2.1.2. Risk identification. Casagrande [7] classified risks into two major types, i.e. the engineering related and the human related. To be more specific, risks of tunnels at operation stage are shown in Table 1.

| Categories                      | Consequence                         | Primary reason                  |
|---------------------------------|-------------------------------------|---------------------------------|
| Engineering related risks       | Structural failure                  | Poor structural health condition |
|                                 | Seepage                             |                                 |
|                                 | Fire                                | Equipment failure               |
|                                 |                                     | Vehicle failure                 |
|                                 | Pounding                            | Weather / Geological hazards    |
| Human related risks             | Fire                                | Vehicle accident                |
|                                 |                                     | Leakage of hazardous chemicals / materials |
|                                 | Pounding                            | Arson / Terrorism               |
|                                 |                                     | Poor management                 |

2.1.3. Critical risk scenarios identification and sensitivities analysis. Investigation of 802 tunnel accidents in China, from 2006 to 2019, shows that 54% of the accidents are caused by vehicle accident or vehicle failure, and 39% of which results in fire [8]. Besides, fire events are also caused by leakage of hazardous chemical such as flammable liquids. Therefore, fire events in tunnels are the most critical risk that needs to be considered.

2.1.4. Risk assessment. Quantitative risk assessment (QRA) is proposed to ensure the effectiveness of the risk management. It is a method to quantify the degree of risks through a systematic examination of the hazards that threaten the safety of tunnels. The risk of event A is the multiplication of the annual probability of the hazard’s occurrence and the resultant consequences due to the hazard’s occurrence, as shown in equation 1 [9].

\[ R(A) = P(A) \times C(A) \]  

where P(A) is the probability of the occurrence of event A, and C(A) is the corresponding consequence.

2.1.5. Risk consequences (or probability) analysis. Risk consequences of tunnels are commonly determined by fault tree analysis (FTA), which was used as a deductive analysis of the likelihood of the casual sequences through mapping the relationship between failure (top event, in this paper, failure refers to fire event), sub-systems and fire safety design elements using Boolean logic.
2.2. Limitation in current risk management

The abovementioned procedures are quantitative risk management that can be hardly understood by decision-makers and on-site workers, who are more likely to use intuitive interface, i.e., fire management system.

On the other hand, the primary principle of fire risk management in China is prevention, followed by extinguishment. Therefore, setting up reasonable fire monitoring system in tunnels is crucial in fire risk management, which can prevent fires from spreading and reduce fire risk since the beginning.

For conventional monitoring systems, the observed events are often too late to be reported. Therefore, risks cannot be well-managed with conventional approaches. In a word, developing a smart system capable of sensing fire at early stage is necessary. In this way, the fire events of tunnels can be detected in real time and the decision-makers can be informed simultaneously.

3. Smart fire monitoring system

An integrated smart fire monitoring system consists of cameras, edge gateways and ZigBee network. It should be noted that the system introduced in this paper is mainly applied to tunnels as a typical geo-structure in urban areas.

Current fire alarm sensors, such as infrared or optical based sensors, need close proximity to the heat, fire and smoke so as to be activated, which gives lagged response to fire events in tunnels. Alternatively, the camera, as a typical vision-based sensor, is widely used, which will provide several advantages over the traditional ones, such as lower cost, faster response, wider coverage, and fewer human activities. Videos and images captured by the camera are sent to the edge gateways through wired network to ensure transmission rate.

Early fire detection in the context of risk management can be a challenging problem due to varying lighting conditions, shadows, and the movement of fire-colored objects. Thus, there is a need for an algorithm that can achieve better accuracy in the abovementioned scenarios while minimizing the number of false alarms. To achieve this goal, Convolutional Neural Networks (CNNs) and a devised fine-tuned architecture for early fire detection for effective fire risk management systems is developed and embedded in the edge gateways. After successful fire detection, alert is sent to the risk management system via ZigBee network.
3.1. Camera
A network camera with good low-light performance is selected in this case to adapt to lighting environment in tunnels. It is also capable of capturing clear image against strong back light. The maximum resolution of video output is $2560 \times 1440 @ 25$ fps, which offers excellent-quality videos to testing.

For validation, another network camera with thermal and optical bi-spectrum is selected in this case. The camera features high sensitivity thermal module and high-resolution video (same as the first one) output. A basic fire-detection algorithm is embedded in the camera, making fire up to 40m in distance detectable.

3.2. Edge gateway embedded with CNN-based fire-detection algorithm
CNN is one of the most widely used algorithm in image recognition problems and requires a lot of training data due to the large number of parameters needed to properly tune these networks before a target model is achieved to detect fire at early stages. In addition to this, the proposed CNN-based model learns details at small scales, enabling it to detect fire even at small scale.

3.2.1. Model structure. The model used in this case has a similar structure to the AlexNet model [10], with a total of five convolution layers, three pooling layers, and three fully connected layers. As input, the model receives color images, and adjusts the image to size of $227 \times 227$ (AlexNet model requires $224 \times 224$ pixels). In the first convolution layer, 96 kernels of size $11 \times 11 \times 3$ are applied to generate FeatureMaps sized $55 \times 55 \times 96$. The first pooling layer selects maximum activations from these FeatureMaps in small neighborhoods of $3 \times 3$ with a stride of 2 pixel. The second convolution layer consists of 128 kernels sized $5 \times 5 \times 48$, followed by a max pooling layer similar to the first one. It is followed by a stack of 3 consecutive convolution layers with 384, 192, and 128 kernels, respectively, all sized $3 \times 3$. The last pooling layer is similar in operation to the first two pooling layers. At the end, there exist three fully connected layers each having 4096, 4096, and 2 neurons (corresponding to the number of classes). 1000 float values are outputted as predicted results. Table 2 shows the number of parameters in each layer. A total of 57,277,728 parameters is generated in this model.

| Layer | Number of groups | Number of kernels | Size of kernel | Total number of parameters |
|-------|------------------|------------------|---------------|---------------------------|
| C1    | 1                | 96               | $11 \times 11 \times 3$ | 34,848                   |
| C2    | 2                | 128              | $55 \times 55 \times 48$ | 307,456                  |
| C3    | 1                | 384              | $3 \times 3 \times 256$ | 885,120                  |
| C4    | 2                | 192              | $3 \times 3 \times 192$ | 663,936                  |
| C5    | 2                | 128              | $3 \times 3 \times 192$ | 442,624                  |
| FC6   | 1                | 4096             | $6 \times 6 \times 256$ | 37,752,832               |
| FC7   | 1                | 4096             | 4096          | 16,781,312               |
| Output| 1                | 1000             | 4096          | 409,600                  |

3.2.2. Training details. The training is performed using the dataset with 2931 images (1215 fire and 1716 non-fire) from Durham University. A set of selected image is shown in figure 2. The database is divided into 5 groups, in which 20% of the data is used for training and 80% for testing. The model is trained by the system with following specifications: Intel Core i7 CPU with 40GB RAM and NVIDIA Quadro T1000 (Turing) GPU with 4GB memory, enabling the proposed algorithm to process video at approximately 15 frames per second (fps), which is almost sufficient to detect early fire (the camera is working on 25 fps).
3.3. ZigBee network

China has been through times of rapid urbanization process, and has witnessed the set-up of many tunnels. For such tunnels in operation, it is often impossible to establish a private wired connection between abovementioned edge gateways and the risk management system. Thus, a reliable wireless connection is needed. ZigBee is a common wireless network solution to many indoor and outdoor scenarios, which is ideal in this case.

3.3.1. Topology of ZigBee network. ZigBee is based on the IEEE 802.15.4 standard and has three typical types of network topology for data transmission (the star, the tree and the peer-to-peer mesh) [11], as illustrated in figure 3. The tree-shaped topology in this case is ideal for ‘strip’ structures such as tunnels, which is used in this case.

3.3.2. Coverage. The preliminary test in a dark environment with strong back light (a simulation to tunnel environment) shows that a camera can cover the distance of 40 m approximately. To ensure reasonable response rate (<1s), five cameras in maximum can be connected to each edge gateway because of the limit of calculation speed and accuracy. Five edge gateways in maximum, as ZigBee end devices shown in figure 3, can be connected to a ZigBee router because of the restriction on transmission distance. Therefore, a ZigBee router can roughly cover the distance of 1000 m. A typical roadway tunnel in Shanghai is about 3-4 km in length, which needs 3-4 ZigBee routers in total connected to one ZigBee coordinator in each direction. The ZigBee network topology and maximum coverage of each component in this case is shown in figure 4.
4. Conclusions
Though geo-structures in China have developed rapidly, less attention is paid to risk control, which results in the lagged response to risk events. In this paper, risk management of tunnels is first discussed. The advancement of technology makes it possible for cameras to detect fire at early stage, which can be helpful to risk management, avoiding huge economic and human losses. Therefore, an integrated smart fire monitoring system with deep learning and ZigBee technology is proposed. A preliminary test shows that the smart fire monitoring system can process the video at 15 fps and detect fire up to 40m in distance. With rapid response, it will greatly improve the fire safety level of tunnels by stopping fire from spreading. Future research will focus on the optimization of deep learning algorithm to make detection faster in response (to reach at least 25 fps) and more sensible (even in longer distance). Besides, it is necessary to establish the training model for the smoke detection to further improve the robustness of fire monitoring.

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