A Study on Excavator Detection to prevent gas lines digging accident based on Faster R-CNN and Drone/AR

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Research Article

A Study on Excavator Detection to prevent gas lines digging accident based on Faster R-CNN and Drone/AR

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Abstract

Recently, damage accidents and damages during urban gas pipe excavation work have been increasing. Based on the Faster R-CNN AI model, an intelligent object recognition technique, excavators are detected in real-time images transmitted from drones and the excavation site is combined with GIS and Augmented Reality (AR) to monitor the excavator location after overlaying it on the map in real time. For intelligent architecture, Client Part is a drone, iPad app, and Server Part is designed as a GIS/AR and AI analysis model. Verification of accuracy was carried out by self-verification and on-site test bed verification. It has increased its ability to implement research by reflecting Real World's environment where regulatory sandboxes are applied. It has been confirmed that it is not unreasonable to apply to the site with an accuracy of about 94% and that the low detection rate, especially due to the nature of the industrial site, suggests that the research is successful. Approximately 58% of the time required for vehicle circuit inspection was reduced. This paper is expected to help develop safety management as the first case in Korea and abroad that combines drones with AI object recognition technology and GIS/AR technology into the urban gas safety management sector.

Keywords: Faster R-CNN, ResNet, Augmented Reality, Excavator Detection, Drone, GIS, AI Platform

1. Introduction

The rate of accidents occurring during the excavation of city gas pipelines is rapidly increasing while the number of broken pipelines is rising. According to the statistics, recent accidents are maintaining double digits, and accidents are occurring in the process of unauthorized excavation, so measures are required to eradicate similar accidents. All excavators are required to report to the Excavation One Call System (EOCS) prior to excavation work in accordance with the Urban Gas Business Act, but there are still many unreported excavation works, which often lead to accidents during excavation work. In addition, although security personnel of related organizations are required to be present during excavation work, there are many cases in which accidents occur due to non-attendance. It is interpreted that this is because there is a limit to the safety inspection and the awareness of the reporting system is low. It is necessary to promote the reporting system and strengthen education for excavators and users [1,2].

The excavation report system is designed to prevent accidents by accurately informing the location of underground gas pipes before the construction is carried out, as the number of underground facilities such as water supply, electricity, telecommunications, and gas increases. The targets of the excavation work are all kinds

of land excavation works, including excavator work, file cutting, and auger work, which are intended to be excavated in areas where urban gas projects are licensed. In the case of excavation, the city gas company must be contacted to guide the location of the pipe in the presence of the staff, conduct the test excavation until the pipe is visible, and the same punishment can be imposed if not reported.

According to the standard safety management regulations, in principle, it is necessary to conduct a circuit inspection of the excavation site at least once a day, and for the pipes exposed due to the excavation work, perform it at least twice a day, and conduct a circuit inspection according to the scale, process and risk level of the excavation work. Subject to the tour inspection are the main building and supply pipe of urban gas, and excavation works within the urban gas supply area. Matters to be checked include gas leaks in pipes exposed due to excavation work, ground subsidence in the upper part of the ground where the pipes are buried, compliance with legal procedures for excavators, and follow-up measures when identifying and discovering unauthorized excavation work. In the case of vehicle inspection by the urban gas industry using vehicles to inspect a wide range of regions, problems such as blind spots caused by residential development zones, alleys, residential areas and market streets, limited inspection vehicle safety accidents once a day [1,2].

In this study, we derive the current status and problems for urban gas excavation accidents and vehicle circuit checks as a prior study. As a solution to the identified major problems, major technologies of the Fourth Industrial Revolution are applied in convergence. In other words, we apply the ResNet CNN-based Faster Region-based Convolutional Neural Network (FasterR-CNN) as an object-aware AI model to address the problems of urban gas pipeline excavation and vehicle circuit inspection. The excavator can be easily detected from real-time images transmitted from the drone to understand the progress of the excavation site, and the location of the gas pipe is overlayed on the map to check whether the excavation work is carried out near the gas pipe burial site in real-time. Furthermore, for the circuit inspection of drone utilization, an empirical test environment is established with special permission for real-class regulation sandboxes as a prerequisite.

The order of this study examines the current status and problems of urban gas pipe drilling, the current status and problems of vehicle circuit inspection of urban gas pipes, and the regulatory sandbox system. In Chapter 3, we consider the Faster R-CNN object recognition model, augmented reality, and GIS system, a convergence and composite IT technology study related to the Fourth Industrial Revolution. Based on this, we establish the direction of the research to improve the problems derived. Based on the research direction, the research is conducted with the IT architecture design, implementation, data preparation and learning (Fine Tuning), and verification steps. Chapter 4 performs self-verification, on-site empirical verification by regulatory sandboxes for effectiveness verification. Finally, Chapter 5 aims to conclude this study by organizing the deficiencies and limitations of this research project and establishing the direction of development in the field of safety management for future research tasks and urban gas ecosystems.

II. Related research

1. A Prior Study on the Excavation of Urban Gas Piping

A. Excavation status and problems

Recently, the rate of accidents that occur during the excavation of urban gas pipes has been soaring as the damage to buried pipes has been on the rise. According to statistics over the past five years, accidents remained slightly declining from eight in 2016 to seven in 2017 and six in 2018. However, the number has soared to 14 in 2019 and remained in double digits, recording 11 in 2020. Moreover, recent accidents have occurred in the process of unauthorized excavation, requiring measures to eradicate similar accidents. Under the Urban Gas Industry Act, all excavators are required to report to the Excavation One Call System (EOCS) before excavation, but many unreported excavation works are still underway, leading to accidents during excavation work. This can be attributed to the limited safety inspection and low awareness of the reporting system. Promotion and education of the reporting system for excavators and users are also needed.

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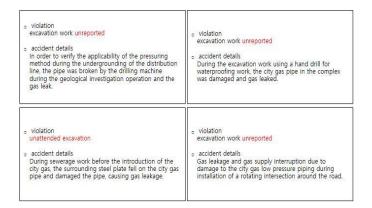


Fig 1. Excavating Work Accident Example

The excavation report system is designed to prevent accidents by accurately informing the location of underground gas pipes before the construction is carried out, as the number of underground facilities such as water supply, electricity, telecommunications, and gas increases. The targets of the excavation work are all kinds of land excavation works, including excavator work, file cutting, and auger work, which are intended to be excavated in areas where urban gas projects are licensed. In addition, the excavation must be conducted after contacting the city gas company to guide the location of the pipe in the presence of the staff until the pipe is visible, and the same can be punished if not reported and discretionary excavation without request for admission [1,2].

B. Current status and problems of vehicle circuit inspection

According to the standard safety management regulations, the excavation site is inspected at least once a day, and pipes exposed to excavation work are conducted at least twice a day, and the head of the department in charge decides how to inspect the excavation work according to the size, process, and risk. Subject to the tour inspection are the main building and supply pipe of urban gas, and excavation works within the urban gas supply area.

Matters to be checked include gas leaks in pipes exposed due to excavation work, ground subsidence in the upper part of the ground where the pipes are buried, compliance with legal procedures for excavation workers, and follow-up measures when identifying and discovering unauthorized excavation work. In the case of the urban gas industry's vehicle tour inspection using vehicles for a wide range of regional tour inspections, problems such as residential development zones, alleys, residential areas and market streets, road traffic laws, limited checks relying on narrow views of vehicle drivers, single checks per day, and risk of vehicle safety accidents [2].

C. Regulatory sandbox system

It is a system that exempts or suspends existing regulations for a certain period of time when new products or services are released in new industries and new technologies. If you apply for the application of regulatory sandboxes for new products and services, you can exempt and suspend regulations due to pilot projects and temporary permits without revising the law, and then post-regulate products that have not been released due to regulations. It is named Sandbox by giving an unregulated environment like a free playground and allowing various ideas to be applied in it [2].

2. Convergence and Combined IT Technology Study on the Fourth Industrial Revolution

A. Faster R-CNN Artificial Intelligence Model

Fast R-CNN is one of the Deep Learning Object Detection (Object Detection) networks based on Convolution Neural Network (CNN) and has been published with improved accuracy and speed since the 2014 R-CNN model and the 2015 Fast R-CNN model. The biggest feature of Faster R-CNN is that it is added in place of the previous method, Selective Search (RPN) process, showing very large time savings. Thus, Faster R-CNN

has a shared RPN network that detects object candidate regions and Fast R-CNN network that extracts and classifies features of object candidates, significantly improving accuracy and speed over previous models. The RPN network operates in a sliding window manner, which travels around the candidate area of objects, calculating and detecting them. Each individual sliding window is designed with an anchor box of varying sizes and aspect ratios. Faster R-CNN consists of a whole four-step process. The first step, Input, is to extract the initial image via ConvNet and then forward it to the RPN. The second stage, the Region Proposal Network (RPN) step, receives a feature map as an input, goes through a convolution process once more with a filter of size N x N, in which the Region Proposal is obtained for each anchor. Another convolution process in the Region Proposal (RP) results in class and coordinate. The third stage, RoI Pooling, uses RoI Pooling to perform Resize so that the box size can be passed to the full-connected. The fourth output stage derives classification and regression results in the same way as Fast R-CNN [3-11,19].

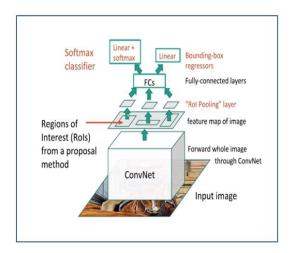


Fig 2. Faster R-CNN Model Architecture

B. Augmented Reality.

Augmented reality is a field of virtual reality (VR) and is a computer graphics technique that synthesizes virtual objects or information in an actual environment to make them appear as if they exist in the original environment. It is frequently used in digital media. Since augmented reality is essential to process visual information in reality, image and image processing technology is required to apply augmented reality technology development.

The most widely applied technology for this purpose is OpenCV. As a kind of library, OpenCV supports major PC and smartphone operating systems and supports various language interfaces. Like the filters of Photoshop, it provides various functions for image and image processing, and it is an appropriate technology for the realization of augmented reality technology because it focuses on real-time processing [12,13].

C. Geographic Information System (GIS)

GIS is an information system that converts geographic information necessary for real life into computer data and uses it efficiently. GIS provides various types of information such as maps, diagrams, and pictures by integrating and managing location data, spatial data, and attribute data for objects with geographic locations. In a broad sense, it refers to an information system for a series of manipulations from observation and collection of geographic information necessary to support decision-making ability, to preservation, analysis, and output. GIS has a wide range of applications as it handles all data closely related to real life. Looking at the city gas field among the fields of application of GIS, the 4th industrial revolution is being realized by combining drones, apps, and 3D technologies with GIS. In addition, GIS is being applied to systems that visualize the location information of facilities such as city gas pipelines, static pressure devices, valves, and meters, and detect anomalies through sensors and monitor them in real time. GIS is actively used to predict and prevent future

events by analyzing data such as past and present conditions, events, and accidents based on location information of facilities [14-16].

3. Establish the research direction

In order to solve the problems of city gas excavation accidents and vehicle circuit inspection, which are problems derived from previous studies, the IT technology of the 4th industrial revolution is fused and applied. As for the identified problems, large-scale accidents increased due to non-reporting of excavation and non-attendance of related persons in city gas excavation. It was selected as the key reason for promoting drone circuit inspection technology development as a quick inspection of the excavation site by drones and the determination of the presence of risks in gas pipelines. The technology development promotion utilizes the object recognition AI model, which is an ICT technology, to detect the excavator from the real-time image transmitted from the drone to easily grasp the progress of the excavation site. by overlaying on the map so that it can be checked in real time whether excavation work is being carried out in the vicinity of the buried gas pipeline. A demonstration test environment is established by applying for a drone inspection to the regulatory sandbox.

III. A Study on Intelligent Excavator Detection

1. Overview of building excavator detection model

In order to solve the problems of urban gas pipeline excavation and vehicle circuit inspection, an artificial intelligence-based analysis model is established. Using drones, LTE communication interfaces, GIS/AR, and Faster R-CNN, the entire research architecture is designed, and the excavator labeling is conducted for data acquisition for learning and then empirical field tests are conducted. Furthermore, we establish an empirical exceptional environment (Test Bed) of government-promoted regulatory sandboxes for empirical field verification.

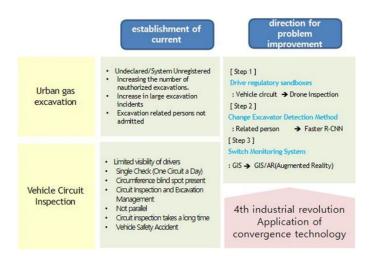


Fig 3. Problem and Improvement Direction

2. Intelligent excavator detection architecture design

For the architecture for intelligent excavator image detection, technologies related to the 4th industrial revolution are fused and applied. Drone, LTE communication network, GIS, AR (augmented reality), and deep learning-based object recognition utilizes Resnet-based Faster R-CNN IT to design and build a research architecture. In addition, the research hardware environment was created as a private cloud environment to pursue operational efficiency and security (data security).

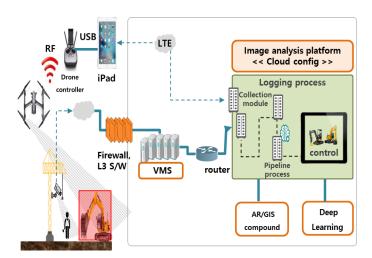


Fig 4. Research Architecture

A. Client Part Design

As a client part, it consists of lithium battery drones and iPads. Drone and controller use RF communication and USB communication between controller and iPad. It is a Payload that is used for drones, and major parts are camera devices and communication modules. The camera is applied with H.264 codec and 60Mbps for HD high-definition. The application mounted on the iPad performs communication with the analysis platform and receiving and expressing recognized excavator information. [17,18]. In other words, drone images are collected using iPads, analyzed on a Cloud basis, and the analysis results are displayed on iPads. Information on drone flight that is collected in real time is meta-information such as communication status, latitude, longitude, altitude, gimbal information, direction, speed, etc. based on TCP/IP. At the same time, video information is collected in real time by RealTime Streaming Protocol (RTSP). Time stamp is applied to synchronization between drone movement and analysis information between telecommunication.

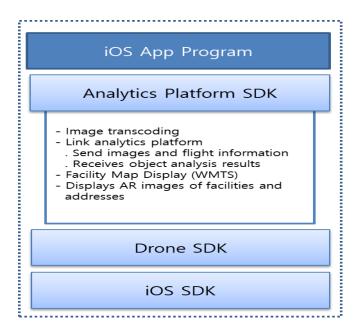


Fig 5. iPad Architecture

B. Server Part Design

It is a function that creates AR rendering information by reflecting GPS location data and GIS gas pipe information in the image received through the drone's high-definition camera and displays it on the web. GIS

gas pipe information must be linked to the API provided by the GIS system, but for data security, it is provided offline and loaded onto the platform.

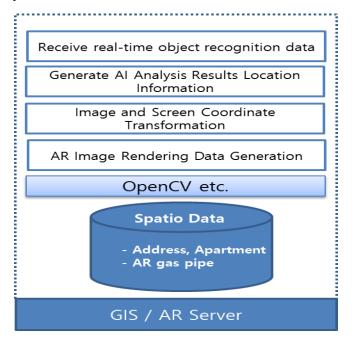


Fig 6. GIS and AR Architecture

Faster R-CNN (Faster Region-based Convolutional Neural Network) consists of a CNN located at the center and two sub-networks that share the final feature map that is the output of this CNN. The two sub-networks correspond to Region Proposal Network (RPN) and Object Detector, respectively. The former is a network that proposes a candidate region for an input image, and the latter is a network that detects an object for each of the proposed regions. In this study, the ResNet 50 (layer 50) model pre-trained for the central CNN of Faster R-CNN is used [20].

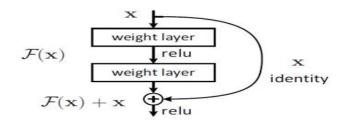


Fig 7. ResNet 50 Architecture

ResNe is an innovative model that solves the gradient vanishing problem even though it is composed of deep layers. The applied Residual Learning is defined in the residual block unit consisting of a 3 x 3 convolution layer and a ReLU layer. In addition, ResNet uses a Skip Connection corresponding to the layer's input as the layer's output.

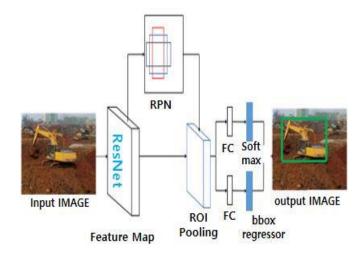


Fig 8. Faster R-CNN Architecture based on ResNet

3. Data set and Fine Tuning

To use the collected images for learning, prepare data by labeling the area corresponding to the excavator in the image file (jpg, etc.). Labeling uses a labeling tool. For the labeled data, the model is trained (Fine Tuning) and evaluated in the order of data set processing.

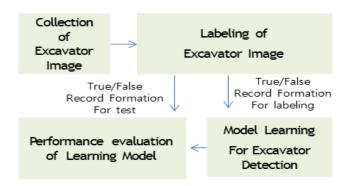


Fig 9. Flowchart of Data Set Processing

The data is obtained from shared images on the Internet, captured videos, and composite images of excavators. In addition, the data is classified into three types for training, verification, and testing. The training set is a data set used during training, and the validation set is used to evaluate the performance of the model created after training and is used for hyperparameter adjustment and learning rate adjustment. do. The test set is used to evaluate the final performance of the trained model.

Number of data set	remarks	
7,000	70%	
2,000	20%	
1,000	10%	
10,000	:=	
	of data set 7,000 2,000 1,000	

Fig 10. Classification of Data Set

IV. Performance evaluation and results

1. Performance Evaluation Overview

Two-step verification was performed to evaluate the performance of the intelligent excavator detection model implemented after design. In-house performance verification based on the collected data and verification by field verification tests were conducted. We applied for a regulatory sandbox for field traversal demonstrative tests by drones and obtained special approval from the government to use the Real World Test Bed.

2. Self-verification result

Evaluation criteria were established and classified into espionage, false positive, and false positive. Classification model performance evaluation indicators include Accuracy, Precision, Recall, and F1 Score. In this study, accuracy was evaluated for the purpose of understanding field personnel. The accuracy was about 94%, and the false positive was confirmed by the low resolution of the image itself.

Evaluation standard	Detailed Explanation		
TN TP	If there is no excavator, but there's no excavator If you have an excavator and you have an excavator		
FP	Detecting that there is an excavator when there is no excavator However, if false positives and false positives exist at the same time, they are treated as false positives		
FN Detecting that there is an excavator but no excavator			

Fig 11. Evaluation Standard

total data (amount)	TP, TN (amount)	FN (amount)	FP (amount)	Accuracy (TP, TN/ total data)
1,000	940	50	10	94 %

Fig 12. Results of Self Evaluation

3. Field Tour Verification Results

As a result of conducting a patrol inspection of the actual service site with a drone, the following effects were found.

- Test conditions: Altitude 100m, flight speed 20km/hr
- Group formation and number of drones: 5 groups of 5 drones
- Test Bed: Classification of service area into 14 areas

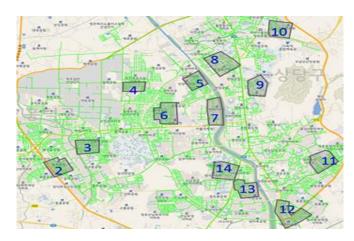


Fig 13. Test Bed

- Field verification test result
- Accuracy level: about 94%, not detected (10%)
- Reduced time required for vehicle inspection by 58%
- Unauthorized excavation detected (Estimated damage per case: about 60million won)

Undetected cases were analyzed to be affected by communication shading areas, shadows, roof colors, and rooftop water barrels, and were found to be heavily affected by personal tendencies such as overlapping course selection of automatic flights during drone flight. It was confirmed that there was no difficulty in applying it to the field with an accuracy of 94%. Considering the problems arising in the case of city gas pipe excavation accidents, the low undetected rate due to the characteristics of industrial sites suggests that the research has been successful.



Fig 14. Quantitative Damage of Digging without Notice

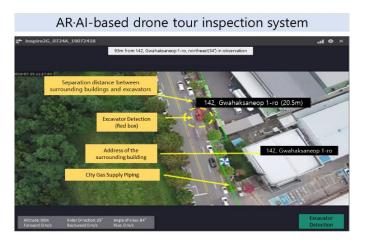


Fig 15. AI and AR Analysis System

V. Conclusion

In recent years, the rate of accidents occurring while the number of damage to buried pipes during city gas pipe excavation construction is drawing an upward curve, and the damage is also increasing. Therefore, in this paper, the current status and problems of city gas excavation accidents and vehicle circuit inspections were derived through prior research. As a solution, the major technologies of the 4th industrial revolution were fused and applied. To solve the problem, the object recognition AI model, which is an ICT technology, is used to detect the excavator from the real-time image transmitted from the drone, so that the progress of the excavation site can be easily grasped, is displayed on the map so that it can be checked in real time whether excavation work is being carried out in the vicinity of the buried gas pipeline. In order to inspect the use of drones, a verification test environment was established by obtaining permission for the regulatory sandbox. As a result of the study, it was confirmed that there was no difficulty in applying it to the field with an accuracy of 94%. Considering the problems that arise in the case of city gas pipe excavation accidents, the low undetected rate (10% level) due to the characteristics of industrial sites suggests that the research has been successful. The application of a drone with object recognition and augmented reality technology to the city gas safety management field was the first domestic and foreign case to be applied to the safety management field, confirming the potential for development of related industries. The limitations of this study are the fact that the AI identification algorithm applied to the study could not be applied in various ways and that the demonstration site was limited to some areas, which should be continuously supplemented and applied. The future plan is to actively promote the creation of a drone circuit inspection ecosystem to promote drone inspection, thereby laying the groundwork for changes to the legal system, such as standard safety management regulations. It is also planning to introduce hydrogen drones that will overcome the 30-minute flight limit of lithium battery drones. In addition to drones, we plan to study how to carry out safety management activities while moving on foot in tablet and smartphone environments. In addition, the ecosystem for the system that monitors the status of unauthorized excavation of city gas pipelines with CCTV at the same time as drones will be carried out, and expansion into safety management-related fields such as excavation construction management, supply facility management, and emergency response at accident sites will be promoted. Technically, ResNet-based Faster R-CNN was applied, but we plan to further study the accuracy of the model by additionally applying pre-trained CNN techniques such as GoogLeNet and AlexNet. Lastly, this study is the first domestic and foreign case where a drone with AI object recognition technology and GIS/AR technology is grafted into the city gas safety management field, and is expected to be a catalyst for the development of safety management.

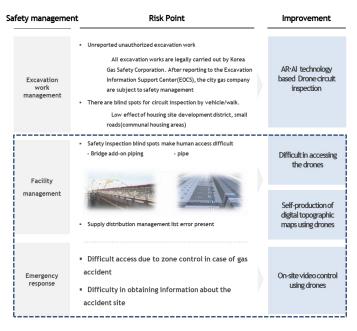


Fig 16. Future Development Direction

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