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Ontological Approach for Automatic Inference of Concrete Crack Cause

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Abstract: The cause of cracks in concrete is traditionally estimated by analyzing information such as patterns and locations of the cracks and whether other defects are present, followed by aggregating the findings to estimate the cause. This method is highly dependent on the expert's knowledge and experience in the process of identifying the cause of the cracks by compiling information related to the occurrence of the cracks, and it is likely that each expert will make a different diagnosis or an expert with insufficient knowledge and experience will make an inaccurate diagnosis. Therefore, we propose automated technology using the ontology to improve the consistency and accuracy of crack diagnosis results in this research. The proposed approach uses information on the crack patterns, locations, and penetration status, as well as the occurrence of other defects, to automatically infer the causes of cracks. We developed ontology that can infer the cause of cracks using the information on their appearance and applied actual cases of cracks to verify the ontological operation. In addition, the consistency and accuracy of the ontology were validated using eight actual cases of crack. The approach of this study can support expert decision-making in the crack diagnosis process, thereby reducing the possibility of various errors caused by the intervention of inaccurate judgments in the crack diagnosis process and improving the efficiency of the crack diagnosis tasks.

Keywords: concrete crack; crack cause; cause estimation; crack diagnosis; ontology

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1. Introduction

Since the invention of artificial cement, it has been used as the main building material in most of the man-made structures on Earth, including buildings. Even today, the number of concrete structures is steadily increasing. Because of its material properties, the performance of concrete decreases over time and cracks occur. Concrete has many advantages, such as ease of manufacture, economy, durability, and so on, but it also has some disadvantages, the most common being that it is prone to cracking. Because cracks in concrete structures have a negative effect on tolerance, durability, waterproofness, and appearance, they can bring about negative problems in the structures [1]. Therefore, cracks in a concrete structure should be diagnosed to prevent exacerbation or recurrence.

Crack diagnosis generally means conducting an investigation into the condition of cracks through an on-site investigation and comprehensively analyzing the investigated data to estimate the cause. Since the repair and reinforcement of cracks depends on what caused them to occur, it is important to accurately estimate the cause to carry out the proper repair and reinforcement. If the cause of the cracks is not accurately identified and improper repair and reinforcement are performed, it will not only be difficult to achieve the effect of repair/reinforcement but also lead to further deterioration of the structure's condition, thus causing significant economic cost.

However, cracks in concrete are caused by highly complex mechanisms influenced by a variety of variables such as the condition of the materials, construction, use of the structure, environment, and structural and external forces, so even technicians with a high knowledge level of concrete and rich experience in using it cannot easily estimate the cause, and different experts often make different judgments [2]. Such problems arise because errors occur in the process of collecting information necessary for estimating the causes of cracks through visual investigation, and human supervision is involved in the process of estimating the cause based on the expert's knowledge and experience by comprehensively analyzing the collected information.

Various studies have been conducted to solve this problem. First, researchers have suggested objective methods of inspection by computers to improve inefficiency in crack appearance investigation methods and to eliminate the subjectivity of human visual inspection methods. These studies have given a high level of accuracy by applying image processing technology or deep learning technology to efficiently extract appearance information such as crack detection along with crack pattern and distribution characteristics. Recently, there have been attempts to apply video technology for safety inspections of buildings in the practice of facility maintenance.

Next, few researches have been conducted to solve problems caused by varying opinions of different experts involved in estimating the cause of the cracks using their knowledge or by non-experts who are unable to make an accurate diagnosis [3,4]. However, there is a limitation in that some of the input information of the systems that have been developed is important in theory but difficult to obtain in practice, and some of the information important for crack diagnosis is not reflected in the developed system.

Although research that solves problems arising from the crack investigation process has been achieved in practice, research to solve problems arising from estimating the causes of cracks based on the results of the crack investigation is insufficient. Therefore, further research is needed to solve problems in which different experts make different diagnoses or non-experts fail to make accurate diagnoses because the work to estimate the cause of the cracks depends on the expert knowledge and experience.

The limitations of the aforementioned process of estimating the cause of cracks can be solved by providing a system that can systematize the common expertise of experts to help make decisions since this expertise is not organized. At this time, the ontology can be viewed as a tool to model experts' knowledge of estimating the causes of cracks for knowledge modeling and retrieval by supporting inference functions as well as for collecting and expressing knowledge [5].

Therefore, this study aims to present a method of estimating the cause of cracks applicable to reality by focusing on solving problems in which different experts can make different diagnoses or non-professionals cannot make accurate diagnoses due to their high reliance on expert knowledge and experience. To this end, we examined the limitations of crack diagnosis work in the existing literature and via expert interviews to extract important information on the practice of crack diagnosis and to realize expertise related to estimating the causes of cracks as ontology.

The composition of this paper is as follows. Section 2 contains an analysis of the existing crack diagnosis process and a discussion of the limitations of existing tasks. Additionally, we examine the applicability of the ontology to crack diagnosis by taking into account the concept of ontological technology used in this study and by examining cases used in the construction industry. In Section 3, we propose an ontology for automating the estimation of the causes of cracks in concrete. Section 4 presents verification of the consistency and accuracy of the proposed ontology to ensure that it and its associated inference rules can work in real-life situations. Finally, Section 5 contains conclusions and a discussion of future work.

2. Literature Review

2.1. Crack Diagnosis Practice

Cracks can occur even when implementing the most thorough regime of maintenance at every stage of the building process. They can adversely affect the durability, functionality, and appearance of a structure, and in severe cases, they can cause serious problems such as structural collapse. Therefore, when cracks occur, it is important to diagnose their cause and to secure the functionality and safety of buildings through proper repair and reinforcement based on the diagnosis results. The crack diagnosis process can be largely divided into the crack investigation and the crack cause estimation.

2.1.1. Crack Investigation

This stage involves the process of detecting cracks in the building through on-site inspections and collecting information necessary for estimating the cause of the cracks through a document survey and a visual inspection. Detection of cracks takes place during an engineer's visit to the building to check the overall damage status of the building, and when he/she finds a crack, he/she conducts a document survey and a visual inspection to assess the condition of the cracks and to collect information to estimate the cause of the cracks. Here, a visual inspection means conducting an on-site investigation to determine the pattern, location, penetration, etc. of the cracks. Meanwhile, the aim of the document survey is to obtain a historical overview of the design, construction, and maintenance of the building through a data review of the design and as-built drawings, specifications, adjacent buildings, suppliers' records, contractors' test records during construction, records of defects and repairs, past and present usage of the building, loadings and subsequent alterations, if any [6]. However, there are many cases in which only a visual inspection is performed because the historical data required for the document survey is not present.

The information that experts need to gather during the crack investigation stage to estimate the cause of the crack is given in Table 1 [6–9].

Table 1. Information Required to Estimate the Cause of Cracks.

Division	Required Information	Example
Crack Status	Generation Period	After concrete placing~Before curing, Within several houres~1 day after curing, Within a few days after curing, More than several ten days after curing etc.
	Crack Location	Slab_Top_Edge, Slab_Top_Center, Slab_Bottom_Edge, Slab_Bottom_Center, Wall_Door_Edge, Wall_Door_Side, Wall_Edge, Wall_Center, Beam_Side_End, Beam_Side_Center, Beam_Bottom_End, Beam_Bottom_Center, Column_Top, Column_Center, Column_Bottom etc.
	Crack Patterns	Complexcity: Single, Complex Shape: Horizontal, Vertical, Diagonal, Stepped, Radial, X-Shaped, Grid, Reticulation, ∧-Shaped, ∨-Shaped Regularity: Regularity, Random
	Penetration status	Surface, Part-through, full depth-through
	Occurrence of Other defects	Exposure/Corrosion: Exposure/Corrosion, Exposure/No_Corrosion, No_Exposure/No_Corrosion Leak/Efflorescence: Leak/Efflorescence, No_Leak/Efflorescence, Leak/No_Efflorescence, No_Leak/No_Efflorescence
Materials and construction conditions	Condition of concrete materials	Cement, aggregate, admixture, water type and trademark, test results, etc.
	Condition of concrete mixing	Rich mix, poor mix, planned mix, executed mix
	Condition of concrete compaction and curing	Concrete mixing time, transportation time, wait time, pouring time, pouring amount, pouring method, pouring order, compaction method, finish method, curing method, etc.
	Records of Concrete Quality Test	Test results of slump, air content, compressive strength, chloride, etc.
	Ground Conditions	Data to check displacement such as staging settlement or differential settlement of structures Backfill time (earth pressure impact) and rising time of groundwater (impact of changes in water pressure variance and heat transfer in underground structures)
	Formworks	Impact of stripping time of staging, deformation due to concrete weight during concrete placement, and heat of hydration of concrete
	Environmental Conditions during construction	Climate, temperature, humidity, wind direction, air volume, solar irradiance, rainfall, snowfall etc., during concrete placement

Table 1. *Cont.*

Division	Required Information	Example
Use/Environmental Condition	Load Condition	Load condition in the structural design report of design drawings, actual loading condition
	Temperature and humidity conditions	Climate, temperature, humidity, wind, solar, rainfall, snowfall, etc.
	Conditions of exposure to chloride	Distance from the coast, wind direction, etc.

2.1.2. Crack Cause Estimation

Experts with a systematic understanding of all areas of construction, such as materials, construction, building environment, and structure, and knowledge of crack generation mechanisms, analyze the various sources of information available (Table 1) collected through investigation to estimate the cause of the cracks based on their expertise and experience.

Previously, researchers have analyzed different cases of cracks and discussed the causes, which has provided a list of pieces of information required to estimate the causes and survey methods, etc. The categorization of the causes of crack occurrence varies somewhat by country and standards but are generally classified as material; construction; use and environmental; external force due to, for instance, structural incompleteness and uneven settlement; and others. In Korea, the classification of causes of cracks proposed by the Ministry of Land, Infrastructure, and Transport in Korea (formerly the Ministry of Construction and Transportation) is being used in practice (Table 2).

Table 2. Classification of crack causes.

Classification			Details	
Materials	Used Materials	Cement	A1	False Setting of Cement
			A2	Heat of Hydration of Cement
			A3	Abnormal Expansion of Cement
		Aggregate	A4	Clay inclusion in Aggregate
			A5	Low Quality Aggregate
			A6	Reactive Aggregate
	Concrete		A7	Chloride in Concrete
			A8	Settlement and Bleeding of Concrete
			A9	Shrinkage of Concrete
Construction	Concrete	Mixing	B1	Non-uniform Dispersion of Admixture
			B2	Long-Time Mixing
		Transport	B3	Change of Mix Proportion at Pumping
		Placing	B4	Inappropriate Placing Sequence
			B5	Rapid Placing
		Compaction	B6	Inappropriate Compaction
		Curing	B7	Loading or Vibration before Hardening
			B8	Rapid Drying during Initial Curing
			B9	Early Age Frost Damage
		Construction Joint	B10	Inappropriate Joint Treatment
	Steel	Arrangement of Steel	B11	Inappropriate Placement of Reinforcement
			B12	Lack of Cover
	Formwork	Formwork	B13	Deformation of Formwork
			B14	Water Leakage (from formwork or ground)
			B15	Early Removal of Formwork
		Support	B16	Settlement of Support

Table 2. *Cont.*

Classification			Details	
Use and Environment	Physical	Temperature and Humidity	C1	Change of Environmental Temperature and/or Humidity
			C2	Difference of Temperatures and Humidity between two surfaces of member
			C3	Repeated Cycles of Freezing and Thawing
			C4	Fire Damage
			C5	Surface Heating
	Chemical	Chemical Reaction	C6	Chemical Reaction of Acid and/or Salt
			C7	Corrosion of Embedded Steel due to Carbonation
			C8	Corrosion of Embedded Steel due to Chloride Attack
Structure and External Force	Load	Long-Term Load	D1	Long-Term Load within Design load
			D2	Long-Term Load over Design Load
		Short-Term (or Living) Load	D3	Short-Term (or Living) Load within Design Load
			D4	Short-Term (or Living) Load over Design Load
	Structural Design		D5	Insufficient Cross Sectional Area or Quantity of Steel
	Support Condition		D6	Differential Settlement of Structure
			D7	Freezing Heave
Others			E	Others

2.1.3. Limitations of Crack Diagnosis Practice

As described earlier, although the related literature and standards categorize and provide required information and causes of cracks, even engineers who have advanced knowledge and rich experience with concrete may not find it easy to estimate the cause through a simple inspection because of the complexity of the crack generating mechanism, and experts may come to different conclusions [2].

Problems that may arise due to these limitations are as follows. First, the diagnosis results are different from expert to expert, which can cause confusion when establishing a crack repair and reinforcement plan and reduce the reliability of the diagnosis results. For example, some experts may estimate the cause of cracks due to concrete material conditions whereas others may blame the structure and external force, which may cause confusion when establishing the repair and reinforcement plan. Second, engineers with insufficient knowledge and experience in crack diagnosis are likely to make inaccurate diagnoses. If the cause of the crack is incorrectly estimated, the safety of the structure cannot be secured due to incorrectly repairing the cracks, and in severe cases, the condition of the structure can be further aggravated. For example, assuming that reinforcement is needed to strengthen a concrete cross-section because of crack occurrence due to an insufficient number of cross-section re-bars in a reinforced concrete building, an engineer whose knowledge and experience regarding crack occurrence mechanisms is lacking could misdiagnose this is a wrong diagnosis of concrete drying shrinkage). Thus, he/she performs a repair via simple surface treatment only that cannot ensure the safety of the structure due to the incorrect repair action taken.

The causes of such a problem are as follows. First, it is easy for subjective judgment or error occurrence in the process of collecting information for crack diagnosis in the crack investigation stage. For ideal crack diagnosis, both information collected through visual inspection of the cracks and information collected through document-based examination (Table 2) is needed. Realistically, for structures that have had a certain period of time since the building completion, related documents such as construction records may be omitted so that information about materials and construction conditions, and use and environmental conditions, cannot be acquired; this means they are either omitted or ascertained by estimation. For example, information in relation to materials and construction conditions such as the condition of the concrete materials and the concrete mixing cannot be known unless the past construction records are available. Thus, the causes of cracks are largely estimated depending on the expert's knowledge and experience using the information acquired through visual inspection of the cracks only in the practice of crack diagnosis. As such, visual inspection data of cracks, such as their pattern and distribution characteristics, become important factors in estimating the cause of cracks [9]. However, visual inspection data are often seen to be rather subjective and error-prone [10]. In this study, a survey was conducted with 15 persons who had experience of crack diagnosis to evaluate the impact to accuracy of crack cause estimation (Impact) and the degree of error occurrence of crack cause estimation (Error) using a Likert 7-point scale. The survey results revealed that both the importance and error levels of crack appearance survey data were high (Table 3). The subjectivity and ambiguity of the cracks' visual inspection information, which can significantly influence the crack diagnosis process, can lead to uncertainty in the crack diagnosis results, which should be improved.

Table 3. Impact and error occurrence of investigation item.

Category	Investigation Item	Impact	Error
Crack Status	Generation Period	3.87	5.60
	Crack Location	6.02	3.87
	Crack Patterns (Complexity, Shape, Regularity)	6.27	5.20
	Penetration status	5.69	4.89
	Occurrence of defects (Exposure/Corrosion, Leak/Efflorescence)	5.58	4.01
Materials and construction conditions	Condition of concrete materials	3.40	2.32
	Condition of concrete mixing	3.86	2.02
	Condition of concrete compaction and curing	3.34	3.01
	Records of Concrete Quality Test	3.26	2.10
	ground conditions	3.02	3.34
	Formworks	3.35	3.01
	Environmental conditions during construction	3.23	3.48
Use/Environmental Condition	Load Condition	4.43	3.59
	Temperature and humidity conditions	4.35	3.04
	Conditions of exposure to chloride	4.05	3.27

Second, it is also easy for human subjectivity (i.e., arbitrary decision-making) in the process that estimates the causes based on the experts' knowledge and experience after analyzing collected information comprehensively in the crack cause estimation stage. As mentioned above, researchers in a large number of previous studies have discussed the causes of cracks after analyzing many crack cases and have presented methods to collect information required to estimate the causes. However, when estimating the causes of cracks in practice, there are no established criteria on how to analyze and combine which information items and finally reach the estimation conclusions of the causes. As a result, experts often make a diagnosis based on their own experience and knowledge. Because even experts with the same level of skills may have different expertise and past experience, they may interpret the same crack differently, and those who lack the related knowledge and experience are likely to make inaccurate diagnoses. The problems resulting from such arbitrary decisions will degrade the reliability of crack diagnosis results or threaten the safety of structures, which is a process that must be improved.

2.2. Previous Research on Crack Diagnosis

Previous studies have been conducted to improve the limits of crack diagnosis discussed above. First, studies have been conducted to extract the visual information of cracks more accurately than the results of human visual surveys by improving the inefficiency of the crack visual investigation method in the crack investigation stage [1,9,11–15]. These researchers argued that manual work by inspectors is laborious, time-consuming, and influenced by subjective behavior of individual inspectors, so objective examination by computer is necessary, and suggested how to efficiently extract visual information such as the detection, patterns, and distribution characteristics of cracks by applying image processing technology or deep learning technology for objective investigation.

In most early studies, crack features were extracted and detected using morphological methods, which are image processing techniques utilizing the images' morphological computation [9,10,16–18]. In other studies, researchers have applied a fuzzy technique to the RGB (Red, Green, Blue) channel values in images by utilizing the contrast in the intensity of the cracks [12,19], improving the contrast characteristics of images by applying a histogram stretching method [20], and using image processing methods such as edge detection and noise removal [21–24]. More recently, with the emergence of artificial intelligence and deep learning technology, studies applying CNN (convoluted neural network) techniques to crack detection have also been conducted [25–31].

The focus of most of the above studies was on collecting objective and error-free visual information by automation based on images to improve the inefficiencies of existing visual inspection methods by the naked eye through the automatic collection of visual information on cracks. Recently, there have been attempts to apply video technology for safety inspections of buildings in the practice of facility maintenance. Nonetheless, few studies have been conducted on reducing the subjectivity of experts in the stage of estimating the crack cause. In these studies, the researchers pointed out that since the crack diagnosis practice is based on the subjective knowledge of experts, the diagnosis results can be different from expert to expert, and because the crack generation mechanism is very complex, non-experts with insufficient knowledge and experience cannot quickly and easily estimate the cause of the crack.

To address these limitations, Lee et al. [3] proposed a system to estimate the causes of cracks occurring in reinforced concrete structures by taking into account nine variables related to cracks (shape, occurrence time, depth, weather, reinforcement corrosion, depth of neutralization, alkali-aggregate reactivity, chloride content in concrete, and humidity). In addition, they used these variables to model a system through data access objects (DAO) to estimate the cause of the cracks and secured objectivity for crack diagnosis work through this system. However, it is difficult to apply these crack diagnosis techniques in practice due to the unrealistic input variables. Among the variables they considered, occurrence time, weather, and chloride content in concrete were information items collected through the documentation survey, and as discussed in Section 2.2, related documents such as construction records for structures have often been misplaced or do not exist, making it difficult to obtain this information. In addition, the form and distribution of cracks were classified simply as single/complex and radial/network/negative in this study. However, in reality, the shape and distribution of cracks vary much more, and it is very important to know which member the crack is located in when estimating the cause of the crack, which the researchers did not take into account.

Meanwhile, Kim et al. [4] proposed a computer-aided system to diagnose the causes of cracks in reinforced concrete structures. They comprehensively considered seven variables (generation period, shape, regularity, cause of concrete deformation, range, weather conditions during concrete placement, and conditions of concrete mixing) presented by the JCI (Japanese Concrete Institute) in relation to crack symptoms by applying the fuzzy set theory to develop a system to help non-experts to diagnose the causes of cracks. This was more applicable in practice because of more detailed classifications of information related to the shape and distribution of cracks that were more simply classified in the study Lee et al. [3]. However, some of the input variables considered in their study are as unrealistic as those in Lee et al. [3]. For example, information such as generation period, weather conditions during concrete placement, and the conditions of concrete mixing are difficult to reflect unless past construction records exist. In addition, the cause of production (contraction, expansion, setting bending shear) and range (material, member, structure) should be estimated and entered through subjective judgments by experts, so there is a high chance that the output results will vary from user to user.

In the above studies, the researchers proposed measures to reduce the subjective intervention of experts who estimated the causes of cracks by automating the estimation process while considering a number of variables comprehensively in relation to crack occurrence. However, some of the input variables considered in the above studies are difficult to collect in practice, which is a drawback as users estimate them through subjective judgment for input.

Although research that solves problems arising from the crack investigation process has been achieved in practice, research to solve problems arising from estimating the causes of cracks based on the results of the crack investigation is insufficient. Therefore, in this study, we want to focus on solving problems in which different experts make different diagnoses or non-experts fail to make accurate diagnoses because the work to estimate the cause of the cracks depends on the expert knowledge and experience.

Thus, the aim in the present study is to propose an automatic inference of crack causes in concrete based on ontology using four pieces of information (crack location, pattern, and penetration or not, and other defects around the crack) in relation to crack appearance, which significantly affects the estimation of crack causes and have a high level of error, to overcome the limitations of previous studies. The method proposed in this study reduces the likelihood of the user's subjective intervention in the process to estimate the causes of cracks by implementing the crack diagnosis mechanism using ontology. In addition, we raise the possibility of practical application compared to existing studies by conducting a study limiting the practical problems to visual crack information.

2.3. Ontology in Construction

An Ontology is an essential technology for expressing and using knowledge in the semantic web field. Although originally derived from philosophy, in the context of computer and information sciences, an ontology defines a set of representational primitives with which to model a domain of knowledge or discourse. The most frequently cited definition of the ontology is that by Gruber [32]: "An ontology is a formal, explicit specification of a shared conceptualization of a domain of interest."

- Formal: Must be machine-readable for the computer to read and process.
- Explicit: The types of concepts and their relationships and constraints are clearly described.
- Shared: Concepts are shared between people–people, people–machines, and machines–machines according to agreed-upon presentation systems.
- Conceptualization: The process of abstracting into a specific model to identify the concepts to be expressed for a specific purpose associated with the phenomenon occurring in the target world.
- Domain: Restricted to the designated areas to which you want to express and share concepts (objectivity and domain dependencies exist).

An ontology is an abstracted model of people's shared ideas about specific concepts in a specific area and represents the expression of knowledge related to the type of concept and the relationship between concepts in a form that people and machines can share. From an information management perspective, an ontology is used to collect and express knowledge by clearly defining and detailing the concepts of resources subject to management. In particular, the ontology can include rules of inference and can be used as a useful tool for systematic knowledge modeling and logical inference [5]. Several studies in the construction industry have used the ontology as a tool for logical inference to solve the problem of complex qualitative judgment [33].

Charlesraj et al. [34] presented an ontology-based knowledge management (KM) framework that enables the selection and allocation of a construction project manager suitable for planned construction projects. Tserng et al. [35] noted that the risks of existing construction projects are managed with subjective decisions by engineers and project managers. They proposed and validated an ontology-based risk management (ORM) framework to address these risks that could infer the causes of risks that arise on the project. Kadolsky et al. [36] identified the problem of the many errors produced during the pre-processing of simulations used to optimize the energy efficiency of buildings and proposed an energy enhanced building information modeling (BIM) framework (eeBIM) in which input data was pre-checked before the simulation phase began and ontology reasoning rules were applied for energy performance analysis. Lee et al. [37] suggested that, although BIM is used for construction management, the intervention of a cost estimator's subjective decisions cannot be avoided in searching for appropriate work items. Furthermore, they proposed an ontological approach that enables the most appropriate work items to be automatically inferred—overcoming the problem of cost estimators' subjectivity.

Wetzel et al. [38] reported that hazard identification activities in facility management (FM) are conducted subjectively based on working knowledge. They presented a framework to support safety management processes that can identify and classify safety attributes and integrate them with BIM data in consideration of FM information flows to address these problems using ontology. Zhang et al. [39] reported that during job hazard analysis (JHA) performance, individual subjectivity, and the time-consuming nature of JHA might be involved in the identification process of potential hazards. Furthermore, they proposed a construction safety knowledge ontology to formalize safety management knowledge and explore the relevance of BIM to develop the interaction between safety management and BIM. Liu et al. [40] proposed a volume-generating ontology to improve the efficiency of the quantity-taking process based on the BIM model. The ontology-based semantic approach was proposed, and the efficiency of existing volume extraction was verified through improved models.

An ontology is a technology that supports logical inference so that machines can express human thinking mechanisms in a way that can be understood. Therefore, applying semantic web technologies to crack diagnosis will eliminate the complex qualitative judgment that occurs during crack cause estimation.

Several studies in the field of facility defect management used semantic web technologies to present a framework for building defect information management. These studies cited the need for a digital representation of existing building defects and a data exchange environment with BIM to use and manage defect information more efficiently.

Lee et al. [41] proposed a framework using BIM and linked data technology to share defect data between heterogeneous data sources, noting that a data feedback mechanism is required to prevent the recurrence of defects. They developed a defect ontology, extracted working context information from beam models, converted BIM data into RDF format, and implemented SPQL queries to enable BIM software applications to consider information generated in defect management domains. Hammad et al. [42] presented a process for integrating the lifecycle inspection, diagnosis, and 3R (repair, rehabilitation, and replacement) action information of a facility with a 3D model. Hamdan et al. [43] have developed the Damage Topology Ontology (DOT), a web ontology that provides terms indicating construction-related damage and its status and relationship with affected construction elements and spatial areas. Furthermore, they proposed extension ontologies for damage classification, damage assessment, and structural mechanics.

The previous studies differ from this study of logical inference because the ontology was used as a tool for securing interoperability and linking across domains. However, given the trend of developing automation technologies using digital representation and computing technologies for crack inspection and diagnosis, with various studies underway to use BIM in the O&M phase, semantic web technologies will be useful for deploying integrated and successful data exchange environments in future studies.

An ontology is a technology that can objectify subjective concepts and express human thinking mechanisms in ways that are intelligible to machines. In the construction field, the ontology is primarily used for the conceptualization and automation of architectural knowledge. Therefore, applying semantic web technologies to the crack diagnosis process will enhance and automate the consistency and accuracy of the diagnosis results to facilitate integration with other technologies in the future.

3. Ontology for Automatic Inference of Crack Cause

3.1. Concept of Automated Inferring Crack Cause

Existing crack diagnosis is made by experts to estimate the cause of the crack by reviewing information such as the crack location, penetration, crack patterns, and whether other defects accompany it, as shown in Figure 1. However, this approach has often led to different conclusions among experts or inaccurate diagnoses. In this study, we intend to use semantic web technologies to develop a method that can consistently infer the exact cause by combining the information given.

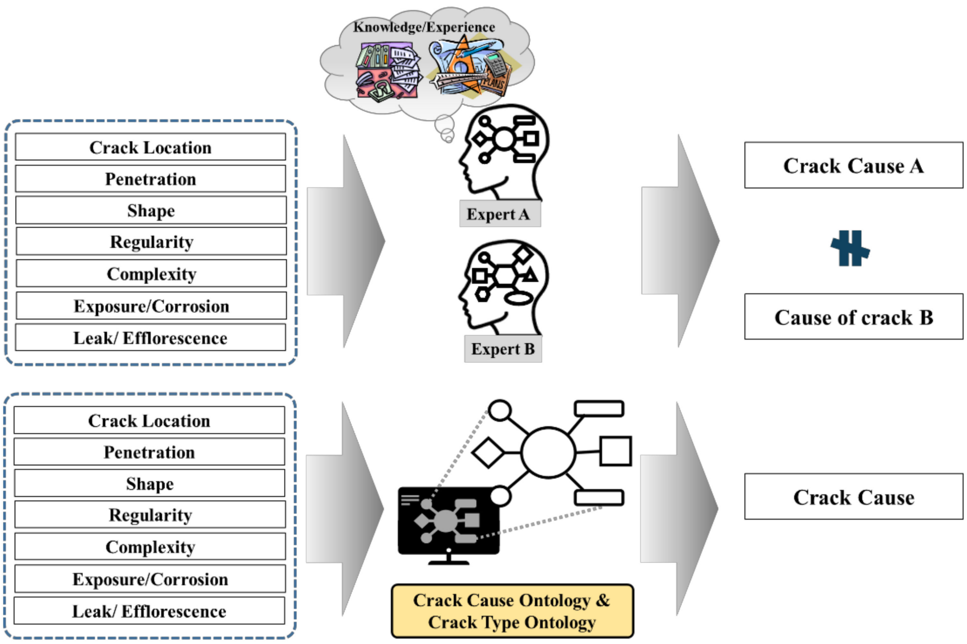


Figure 1. Inference mechanism using ontology.

In this study, elements that determine the type of crack and elements that define the cause of the crack are constructed on a site to recognize the crack information obtained by visual inspection to automate the process of diagnosing the cause of the crack to achieve greater accuracy and consistency than the existing method.

For this automation to be possible, the establishment of "Crack Type Ontology (CTO)", which consists of factors that determine the type of crack, and "Crack Cause Ontology (CCO)", which consists of factors that define the cause of the crack, should be preceded. In this study, class and reasoning rules were defined based on the knowledge of existing literature and crack diagnosis experts related to concrete cracking, and the ontology and reasoning rules were established using Protégé v5.5.0.

The Figure 2 is the overall structure of the ontology to derive the cause from the crack type. Solid lines represent a subclass concept to represent hierarchical relationships between classes, and dotted lines represent relationships between classes and between classes and data, representing object properties that correspond to elements.

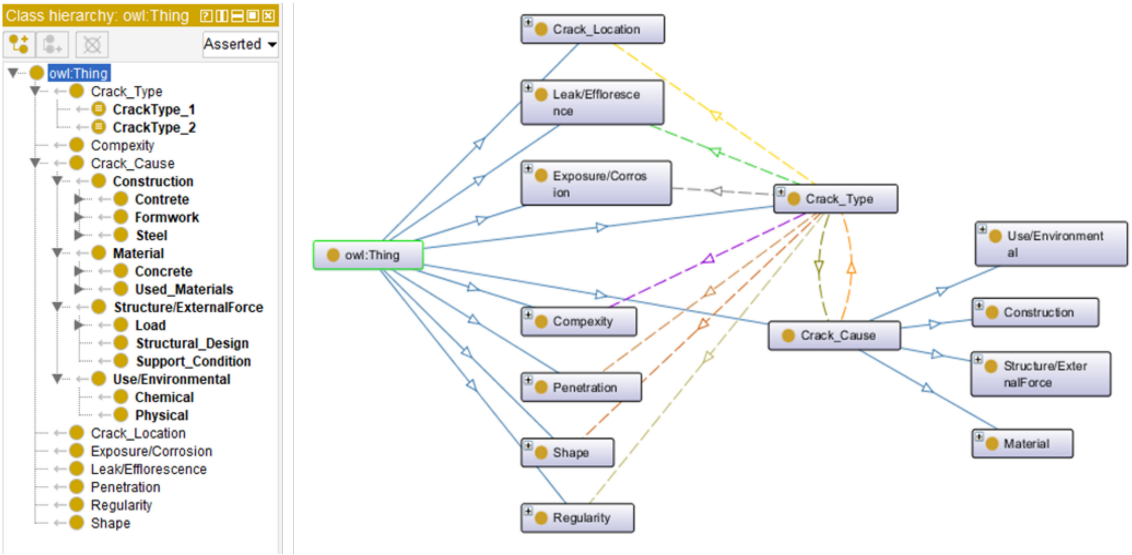


Figure 2. 'Crack Type Ontology' and 'Crack Cause Ontology' for crack diagnosis.

3.2. Definition of Class

The CCO has elements that define the crack cause in a subclass, such as "Material", "Construction", "Use/environmental", "Structure/external force". The CTO consists of classes defined as elements that determine crack types such as "Crack location", "Penetration", "Complexity", "Regularity", "Shape", "Exposure/Corrosion", "Leak/Efflorescence" and "Crack type class" defined by ontology inference rules for class combinations. In addition, the "crack type class" defines the crack cause corresponding to the crack type as the ontology inference rule. Classes and instances defined in the ontology proposed in this paper are shown in Table 4.

Table 4. Definition of Class.

Class	Instances
Crack Location	Slab_Top_Edge, Slab_Top_Center, Slab_Bottom_Edge, Slab_Bottom_Center, Wall_Door_Edge, Wall_Door_Side, Wall_Edge, Wall_Center, Beam_Side_End, Beam_Side_Center, Beam_Bottom_End, Beam_Bottom_Center, Column_Top, Column_Center, Column_Bottom.
Penetration	Surface, Part-through, full depth-through
Complexity	Single, Complex
Regularity	Regular, Irregular
Shape	Horizontal, Vertical, Diagonal, Stepped, Radial, X-Shaped, Grid, Reticulation, Λ-Shaped, V-Shaped
Exposure/Corrosion	Exposure/Corrosion, Exposure/No_Corrosion, No_Exposure/No_Corrosion
Leak/Efflorescence	Leak/Efflorescence, No_Leak/Efflorescence, Leak/No_Efflorescence, No_Leak/No_Efflorescence
Crack Type	Class to define crack type
Material	Cement, Aggregate, Concrete
Construction	Proportion, Transport, Cast in Place, Compaction, Curing, Chipping, Steel, Arrangement,
Use/Environmental	Physical, Chemical
Structure/External Force	Load, Structural Design, Supporting
Crack Cause	Class to define crack cause

3.3. Definition of Property

In order to define the class of the ontology, the existing literature review and expert interview regarding concrete cracks were conducted. The class of 'Crack Cause Ontology' is defined by reflecting the classification of crack causes (Table 2) suggested by the Ministry of Land, Infrastructure and Transport [7]. In addition, the class of 'Crack Type Ontology' was defined by 15 experts in crack diagnosis by reflecting information (Table 3) that indicated that the cause of the crack was highly influential and the error level was high, and detailed by reflecting the results of the existing literature review [2,6–8].

The ontology allows properties and constraints to be established to articulate the relationship between concepts and resources. Properties are divided into object and data properties. Where the former are attributes associating an instance of a class with an instance in another class, the latter associate the class with a particular data type. The properties defined in the ontology of this paper are shown in Table 5.

Table 5. Definition of properties.

Object Property	Domain	Range
Has Crack Location	Crack Type	Crack Location
Has Penetration	Crack Type	Penetration
Has Complexity	Crack Type	Complexity
Has Regularity	Crack Type	Regularity
Has Shape	Crack Type	Shape
Has Exposure/Corrosion	Crack Type	Exposure/Corrosion
Has Leak/Efflorescence	Crack Type	Leak/Efflorescence
Has Crack Type	Crack Cause	Crack Type
Has Crack Cause	Crack Type	Crack Cause

'Crack Type' defines crack type by associating with element classes that determine crack type by object properties (e.g., 'has Crack Location', 'has Penetration', 'has Complexity', 'has Regularity', 'has Shape', 'has Exposure/Corrosion', 'has Leak/Efflorescence'). 'Crack Type' associates with 'Crack Cause' as 'has Crack Type' object property.

3.4. Semantic Reasoning and Query

The crack location, penetration, complexity, regularity, shape, exposure/corrosion, leak/efflorescence information obtained through visual inspection is recognized as one of the crack types and is recommended for the "crack type ontology" as appropriate for the crack type.

For example, the attribute information of cracks such as "Slab_Bottom_Center, Surface Penetration, Complexity, Regularity, Grid Shape, Exposure/Corrosion, and Leak/Efflorescence" is parsed and automatically recognized in the classes of "Crack Location, "Penetration", "Complexity", "Regularity", "Shape", "Exposure/Corrosion", or "Leak/Efflorescence" as an instance. The attribute information of the recognized cracks is recognized as an instance (CT_1) of lower class called "CrackType_1" with the following necessary and sufficient conditions: Slab_Bottom_Center, Surface Penetration, Complexity, Regularity, Grid Shape, Exposure/Corrosion, and Leak/Efflorescence among the lower classes of "Crack Type Class" through inference. Next, the crack cause of "CrackType_1" is the most appropriate crack cause to the crack type "CT_1" among the lower classes of "Crack Cause Class" whose necessary condition is "A2(Material-Used Material-Cement-Heat of Hydration of Cement), A9(Material-Concrete-Shrinkage of Concrete), B12(Construction-Steel-Arrangement of Steel-Lack of Cover)", which eventually diagnoses the crack cause.

For this inference process, the rules of inference must be defined. In this study, various documents [2,6,8], including the specifications of the Ministry of Land, Infrastructure, and Transport [7], were reviewed and in-depth interviews were conducted with three experts with more than 25 years of working experience in crack diagnosis. The rules of reasoning, which reflect the results of the literature review and interview, are as follows:

CT_1 ≡

Necessary and Sufficient

∋ hasCrackLocation has Slab_Bottom_Center
∋ hasPenetration has Surface
∋ hasComplexity has Complex
∋ hasRegularity has Regularity
∋ hasShape has Grid
∋ hasExposure/Corrosion has No_Exposure/Corrosion
∋ hasLeak/Efflorescence has Leak/Efflorescence

Necessary

∋ hasCrackType has A2
∋ hasCrackType has A9
∋ hasCrackType has B12

The validation and reasoning of the ontology utilized HermiT Reasoner ver.1.4.3.456, contained in Protege v5.5.0. Validation shows that the ontology is defined consistently without logical errors on its own and that property information defining the crack type in the lower class of "CrackType_1" is recognized correctly (see Figure 3).

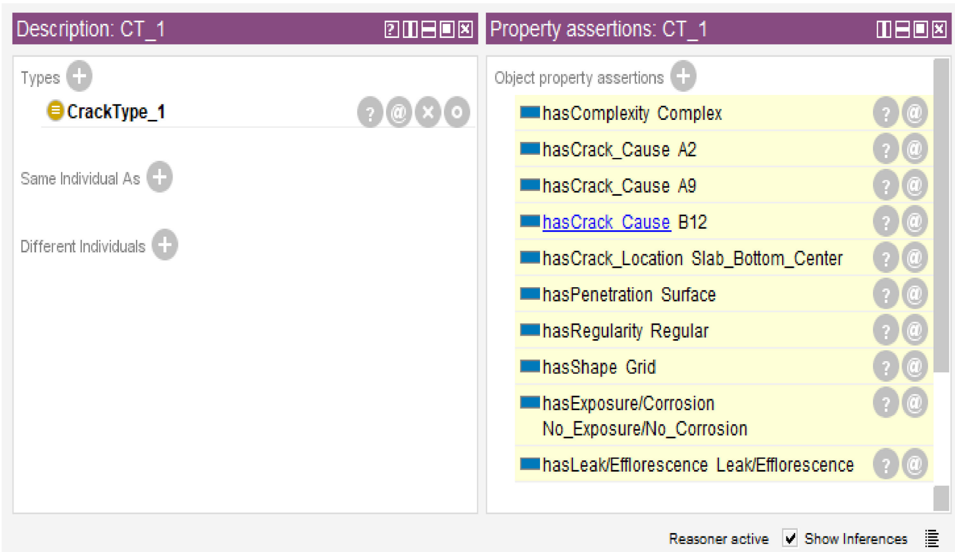


Figure 3. Verification results.

The ontology implemented using the DL Query included in Protege v5.5.0 allows the inference of crack types with the properties of crack types (see Figure 4) and allows the inference of crack causes from crack types (see Figure 5). In other words, if the RDF format contains property information that can determine the class of ontology, it means that the crack type is recognized through the inference process, and the crack cause corresponding to the crack type is recognized.

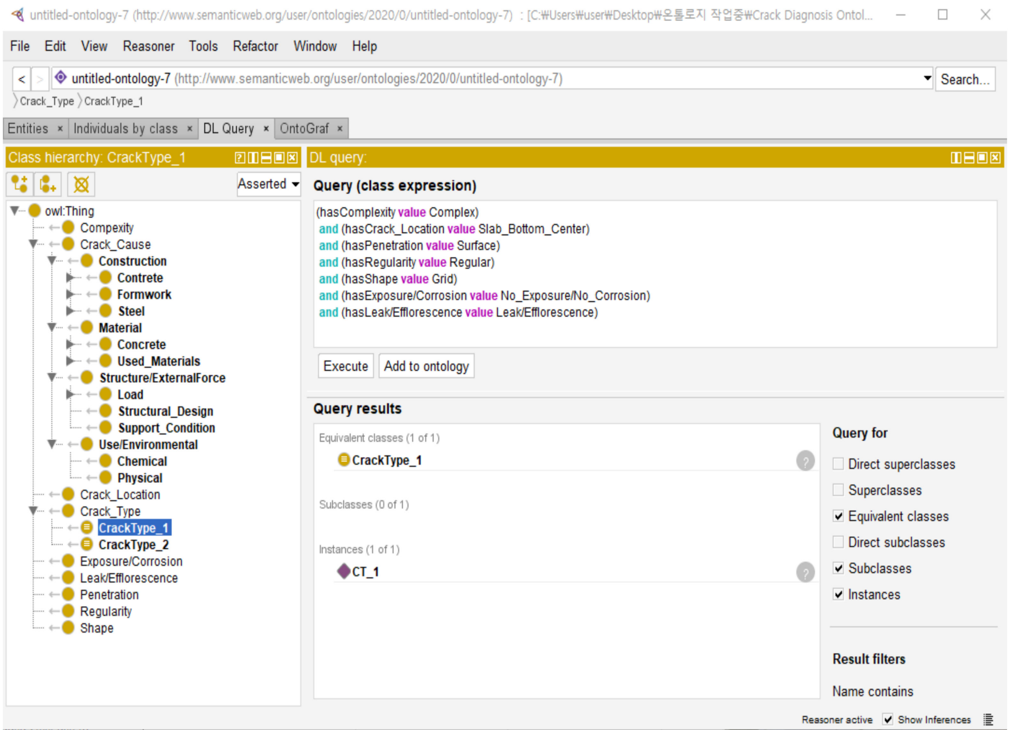


Figure 4. Example of searching for crack type with property information of crack type.

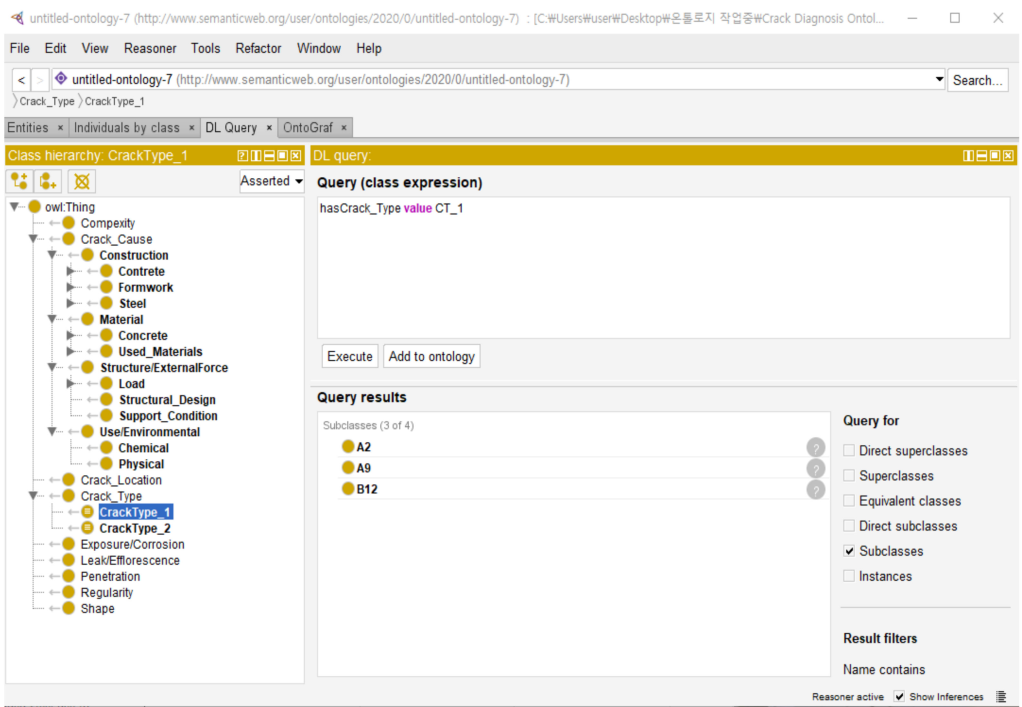


Figure 5. Result of inferring the crack cause from the crack type.

4. Validation

In this study, we propose an ontological approach to infer the causes of cracks. The proposed approach uses information on the crack patterns (complexity, shape, regularity), crack location, penetration status, and occurrence of other defects (exposure/corrosion, leak/efflorescence) to automatically infer the causes of cracks. This method allows engineers to find more accurate and consistent causes of cracks.

To validate the consistency and accuracy of the inferred results, we make a comparison between diagnosis results inferred by the proposed inference mechanism of the ontological knowledge structure and those inferred by the inference mechanism of expert knowledge. We interviewed five engineers who each had more than 9 years of experience in South Korea. We provided the eight actual crack cases to the five engineers, who selected the three most suitable causes of crack for each case. These crack cases consist of images that can identify the pattern of cracks, penetration status, and whether other defects are present, as well as text information corresponding to the location of cracks (see Table 6).

Table 6. Crack case for validation.

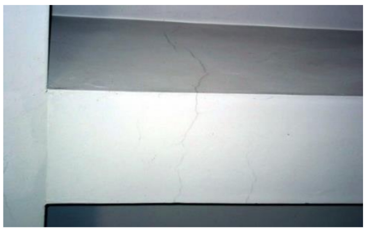
No.	Location	Image	Crack Causes
Case 1	Slab_Bottom_Center		A2. Heat of Hydration of Cement A9. Shrinkage of Concrete B12. Lack of Cover
Case 2	Slab_Bottom_Center		A9. Shrinkage of Concrete C4. Fire Damage C5. Surface Heating
Case 3	Wall_Door_Edge		A2. Heat of Hydraation of Cement A9. Shrinkage of Concrete D5. Insufficient Cross Sectional Area or Quantity of Steel
Case 4	Wall_Center		C1. Change of Environmental Temperature and/or Humidity D5. Insufficient Cross Sectional Area or Quantity of Steel D6. Differential Settlement of Structure
Case 5	Beam_Bottom_End		A9. Shrinkage of Concrete B10. Inappropriate Joint Treatment B12. Lack of Cover

Table 6. *Cont.*

No.	Location	Image	Crack Causes
Case 6	Beam_Side_End		B4. Inappropriate Placing Sequence B5. Rapid Placing D4. Short-Term (or Living) Load over Design Load
Case 7	Column_Top		D2. Long-Term Load over Design Load D4. Short-Term (or Living) Load over Design Load E. Others (Damage of finishing)
Case 8	Column_Center		D2. Long-Term Load over Design Load D4. Short-Term (or Living) Load over Design Load D5. Insufficient Cross Sectional Area or Quantity of Steel

Table 7 shows the results of this comparison. Interview results show that although it is the result of inference of causes of cracks by engineers with considerable experience, there is little consistency. On the other hand, the inference results from the proposed ontology always showed consistent results in the same crack cases. In addition, if the ontology provided was written based on the exact expertise of crack diagnosis task experts, the accuracy of the crack cause reasoning results using it could also be ensured. In addition, since the proposed ontology was built based on the exact knowledge of the crack diagnosis experts, the accuracy of the crack cause inference results using it could also be ensured.

Table 7. Result of comparison.

Case	Traditional Method (Expert Decision)					Proposed Method (Using Ontology)
	A (9 Years)	B (10 Years)	C (11 Years)	D (17 Years)	E (20 Years)	
Case 1	A9 (100%) B8 (20%) B12 (80%)	A9 (100%) B12 (80%) E (20%)	A9 (100%) D2 (20%) D4 (20%)	A2 (40%) A9 (100%) B12 (80%)	A2 (40%) A9 (100%) B12 (80%)	A2 (100%) A9 (100%) B12 (100%)
Case 2	A9 (80%) B8 (20%) C3 (20%)	A2 (20%) A9 (80%) B1 (20%)	A6 (20%) A9 (80%) C1 (20%)	A9 (80%) C4 (40%) C5 (40%)	C2 (20%) C4 (40%) C5 (40%)	A9 (100%) C4 (100%) C5 (100%)
Case 3	A9 (80%) D5 (80%) E (40%)	A9 (80%) D3 (20%) D6 (20%)	D1 (20%) D2 (40%) D5 (80%)	A9 (80%) D2 (40%) D5 (80%)	A9 (80%) D5 (80%) E (40%)	A2 (100%) A9 (100%) D5 (100%)
Case 4	D1 (20%) D3 (40%) D4 (40%)	A9 (20%) D3 (40%) D6 (60%)	C2 (40%) D4 (40%) D5 (40%)	C1 (40%) D5 (40%) D6 (60%)	C1 (40%) C2 (40%) D6 (60%)	C1 (100%) D5 (100%) D6 (100%)

Table 7. *Cont.*

Case	Traditional Method (Expert Decision)					Proposed Method (Using Ontology)
	A (9 Years)	B (10 Years)	C (11 Years)	D (17 Years)	E (20 Years)	
Case 5	A9 (80%) B5 (20%) B7 (20%)	A9 (80%) D1 (40%) D2 (20%)	B11 (20%) D1 (40%) D5 (40%)	A2 (20%) A9 (80%) B12 (40%)	A9 (80%) B12 (40%) D5 (40%)	A9 (100%) B10 (100%) B12 (100%)
Case 6	D2 (60%) D3 (20%) E (40%)	D2 (60%) D4 (60%) D6 (20%)	D5 (40%) B12 (20%) E (40%)	B4 (20%) B5 (20%) D4 (60%)	D2 (60%) D4 (60%) D5 (40%)	B4 (100%) B5 (100%) D4 (100%)
Case 7	A9 (60%) B8 (20%) B10 (20%)	D2 (60%) D4 (60%) D5 (20%)	A9 (60%) D1 (20%) D2 (20%)	A9 (60%) D2 (60%) D4 (60%)	D2 (60%) D4 (60%) E (20%)	A9 (100%) D2 (100%) D4 (100%)
Case 8	D2 (60%) D4 (80%) D6 (40%)	D1 (20%) D3 (20%) D4 (80%)	A9 (20%) D5 (60%) D6 (40%)	D2 (60%) D4 (80%) D5 (60%)	D2 (60%) D4 (80%) D5 (60%)	D2 (100%) D4 (100%) D5 (100%)

5. Conclusions

Concrete cracks have traditionally been estimated by analyzing information such as crack patterns and location, and whether other defects are present, and then aggregating the findings to estimate the cause of the cracks. This method is highly dependent on the experts' knowledge and experience in the process of identifying the cause of cracks by compiling the information related to their occurrence, and it was likely that each expert will make a different diagnosis or an expert with insufficient knowledge and experience will make an inaccurate diagnosis.

Therefore, in this research, we propose automated technology using ontology to improve the consistency and accuracy of crack diagnosis results. Although the information on the crack condition (pattern, location, etc.) has the greatest effect on the accuracy of the crack cause estimation, in many cases it relies only on visual inspection, so many estimation errors occur. To solve this problem, this study presented a methodology to automate the process of estimating the cause of the crack based on the crack state. To automate inference of crack cause, we proposed "Crack Type Ontology (CTO)," which consists of factors that determine the type of crack, and "Crack Cause Ontology (CCO)," which consists of factors that define the cause of the crack. To verify the consistency and accuracy of the built the CTO and the CCO, eight actual cases of cracks were collected, and the results derived from the proposed ontology were compared with the diagnosis results derived by the five crack diagnosis practitioners.

Because an ontology is a technology that allows machines to express human thinking mechanisms and supports logical inference, the proposed approach can remove the matter of complex qualitative guidance that occurs during the crack cause estimation process. As such, the approach in this study can support expert decision-making in the crack diagnosis process, thereby reducing the possibility of various errors due to the qualitative judgment in the crack diagnosis process and improving the efficiency of crack diagnosis work. As a result, it can contribute to the automation of the crack diagnosis process and the improvement of the consistency and reliability of the diagnosis results.

Future studies to improve the completion of this study are as follows. First, the accuracy of the reasoning results needs to be improved. We selected the factors necessary for estimating the cause of cracks and established the inference rules through consideration of the existing literature and expert interviews. Inference rules may vary somewhat from expert to expert, so further expert interviews are needed in future studies to increase the accuracy to the extent available in practice. Second, the future research is needed to develop a system that considers the strength class of concrete, the cement content and the age of the concrete etc. In this study, we proposed ontology to estimate the cause of the crack by using information related to the shape of the crack, but information such as the strength class of concrete, the cement content, the age of the concrete, etc. also greatly affect the formation of cracks. Third, to fully automate the inference process, additional research is needed to automatically extract and input information entered into the ontology. Information entered into the ontology presented in this study should be entered manually. Further research is needed to eliminate the possibility of errors that may occur when entering information manually and to automate the crack diagnosis process as a whole. This could be solved by using drones to acquire images, using deep learning and image processing technologies to automatically detect cracks, and by linking them with technologies that can automatically extract information such as the shape and penetration of cracks, as well as the presence of other defects. Finally, further research is needed to establish an integrated data exchange environment that can be managed with various information of buildings by linking crack investigation data and estimated crack cause data with building information modeling (BIM). Cracks are deeply related to the spatial and structural elements of the building, but most crack data are text-based in PDF, Word, and spreadsheet documents, which can be dispersed [41]. This makes it difficult for multiple stakeholders, including building owners, facility managers, builders, and structural engineers, to search or analyze data. These limitations can be resolved by integrating the crack data with spatial information in the BIM, thereby making more accurate diagnosis and the sharing and reuse of crack cause data obtained through crack cause estimation ontology possible.

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