ICCEPM 2024 https://dx.doi.org/10.6106/ICCEPM.2024.0566
The 10th International Conference on Construction Engineering and Project Management
Jul. 29-Aug.1, 2024, Sapporo

Employing Ontology and Machine Learning for Automatic Clash Detection and Classification in Multi-disciplinary BIM Models

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Abstract: Clashes between architectural, structural, and mechanical, electrical, and plumbing (MEP) systems are unavoidable as each discipline typically develops its own BIM models prior to federation. Commercial model checkers identify these clashes but do not classify them with respect to their severity, requiring every clash to be evaluated manually by the parties involved. Moreover, the assessment of their severity can be subjective and open to misinterpretations. To address these inefficiencies, an ontological approach was employed exclusively for clashes between multi-disciplinary BIM models. For a given clash, the ontology linked two elements, and encompassed their relevant geometric data and topology, which were retrieved using Navisworks and Python mesh packages. The clashes, distinguished as hard and soft, used separate approaches to classify their severity. Hard clashes employed machine learning algorithms to infer their severity based on geometric and project type features. Soft clashes used SPARQL-based rules which have predefined conditions for distinguishing clash severity based on semantic, geometric, and topological features. The ontology was implemented using RDF/OWL standards and programmed in Navisworks as an add-in module. Validation performed on an actual BIM model with 18,887 number of clashes showed that the ontology enabled highly accurate clash severity detection for both hard and soft clashes.

Key words: BIM, Clash Detection, Ontology, Severity Classification

1. INTRODUCTION

In construction management, the introduction of BIM has significantly enhanced the efficiency of clash detection tasks. Despite this, due to the nature of the BIM modeling process, where architectural, structural, and mechanical, electrical, and plumbing (MEP) disciplines are modeled separately and then federated, many clashes still occur and are identified by commercial model checkers. However, the detection focuses primarily on hard clashes, which are physical overlaps between objects, and often fails to detect soft clashes, which address issues such as usability and accessibility (e.g., piping passing through a door opening or closing area), due to their non-geometric nature and reliance on design expertise [1]. Even when clashes are identified, model checkers struggle to accurately classify them by their detailed type and severity, requiring manual evaluation by participants, a process that can be subjective and prone to errors [2].

To address these inefficiencies, this study aims to employ an ontological approach to detect additional clashes in multidisciplinary BIM models and automatically classify their type and severity. The clash types were predefined through expert interviews into 12 detailed types of hard clashes and 13 detailed types of soft clashes, with three levels of severity: Major, Medium, and Minor. To classify their severity, hard and soft clashes employed distinct approaches. Hard clashes utilized eXtreme Gradient Boosting (XGBoost) to infer severity based on geometric and project type features. Soft clashes used SPARQL-based rules which have predefined conditions for distinguishing clash severity based on semantic, geometric, and topological features.

2. RESEARCH BACKGROUND

Previous approaches on automatic clash type classification were primarily divided into inference rule-based and machine learning-based approaches. The inference rule-based approach, a deductive method, involved defining a set of rules to infer their types. For instance, [3, 4] used the ruleset in the Solibri model checker to classify clash types in architectural discipline, while [5] applied a Bentley Navigator-based ruleset to classify piping clash types. However, these rule-based methods depend on experts to manually establish the rules, making them highly specialized and limited in scope.

Recently, there has been a shift towards employing machine learning algorithms to classify a broader spectrum of clash types. [6] applied four machine learning algorithms to classify clash types in MEP discipline, [7] applied six algorithms to classify 'irrelevant' clashes. [8] applied an ensemble technique on six elements to classify clash types with 0.90 ACC, and [9] utilized YOLO v5, an image classification algorithm, to identify whether the clash contains major elements.

However, previous approaches have relied on a limited set of manually selected variables for classifying clash types, which does not adequately encompass the wide variety of types encountered in practice and excludes soft clashes from their detection range. To address these issues, this study extracted various clash information and storing it in an ontology. This enables a thorough analysis of both the detailed type and severity of all clash instances, including soft clashes, thus offering a more comprehensive approach to clash detection and classification.

Table 1. Criteria of clash type and severity

Hard clash			**Soft clash**		
No.	**Clash type**	**Severity**	**No.**	**Clash type**	**Severity**
1	Clash between architectural-structural elements	Major	1	Existence of unnecessary element in a specific space	Major
2	Clash between architectural-MEP elements		2	Securing door opening and closing range	
3	Clash between structural-MEP elements		3	Securing legal ceiling height	
4	Clash between main MEP elements		4	Passing MEP elements in ladders and railings	
5	Clash between utilities in main MEP		5	Distance between beam and duct elements	Medium
6	Clash between non-main MEP elements	Medium	6	Distance between duct elements	
7	Clash between utilities in non-main MEP		7	Distance between duct and pipe elements	
8	Clash from modeling overlap between architectural elements	Minor	8	Distance between pipe elements	
9	Clash between architectural elements		9	Distance between pipe and architectural ceiling elements	
10	Clash from modeling overlap between structural elements		10	Placing MEP elements under the ceiling	
11	Clash between structural elements		11	Missing fitting between utilities	Minor
12	Clash from not sleeve modeling		12	Attribute errors in MEP elements	
-	-		13	Missing attribute information	

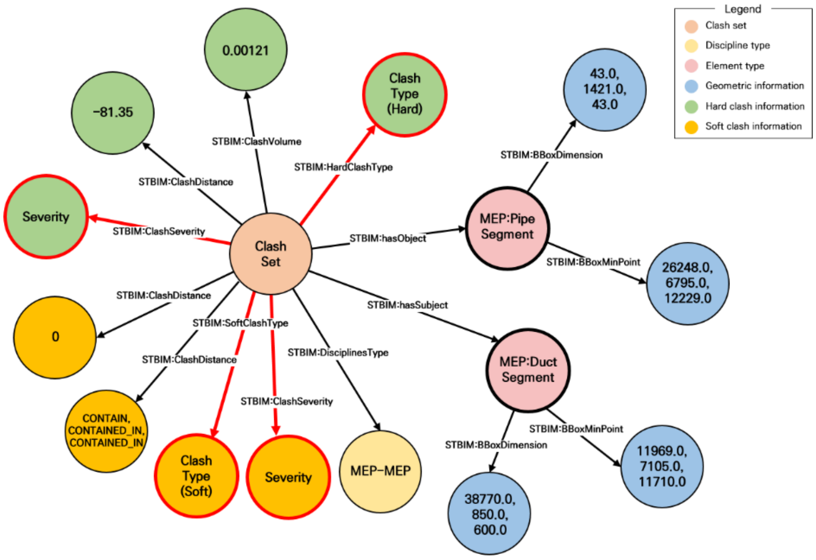

Figure 1. Ontology for clash set representation

3. METHODOLOGY

This study was conducted in four stages: establishing criteria for classifying clash types, constructing an ontology, classifying clash types and severity, and developing their respective modules. Clash types were classified into 12 hard clash types and 13 soft clash types based on expert interviews and design quality control checklists. Then, each type was further categorized into Major, Medium, and Minor levels of severity (Table 1). Then, an ontology schema was developed to represent the relationship between BIM elements in the form of a Resource Description Framework Schema (RDFS), which was implemented using the 'RDFlib' library in Python. Figure 1 shows an example of the constructed ontology, where the discipline types, semantic, geometric, and topological features are interconnected and stored as nodes, with the 'Clash Set' node at the center representing the relationship between two elements. Also, the 'Clash Type' node is designed as a placeholder to include the classification results from the subsequent phase. The geometric and physical information were extracted using Python libraries PyMesh, Trimesh and IfcOpenShell.

To classify clash types, we used separate approaches for hard and soft clash. For hard clashes, the information within the ontology served as variables, and XGBoost, a decision tree-based machine learning algorithm, was utilized to classify the types. Soft clashes employed SPARQL, an RDF-specific query language, to define custom rules for the clash types listed in Table 1 for their detection and classification. The classification results were then embedded into the ontology and programmed as an add-in module within Navisworks to visualize the classification results in conjunction with the BIM model.

4. RESULTS

Validation was performed on an actual BIM model with 18,062 hard clashes and 825 soft clashes which labelled by experts. XGBoost achieved a classification accuracy (ACC) of 0.92 for hard clashes, while SPARQL-based rules classified soft clashes with 1.00 ACC. Finally, the inferred severity was added to the ontology, which was programmed into Navisworks as an add-in module, and SPARQL-based queries confirmed that the clash information was output correctly (Figure 2).

5. CONCLUSION

To overcome the limitations of conventional clash detection methods, this study adopted an ontological approach to identify additional clashes and to classify their specific types and severities. By developing an ontology with RDF structures containing clash-related information, the study utilized XGBoost for classifying types of hard clashes, while SPARQL query-based rules were applied to detect and classify soft clashes. These results showed that the ontology enabled highly accurate clash severity detection for both hard and soft clashes, with rapid access to the results. And as the size and complexity

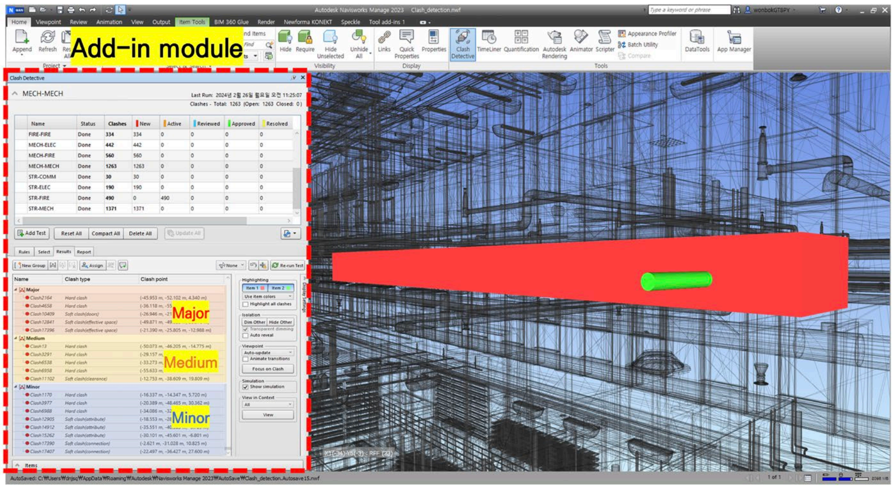

Figure 2. Navisworks add-in module

of BIM models increase in practice leading to more frequent clashes, the significance of this automated approach is expected to grow even more. Future research will aim to identify additional variables to enhance the accuracy of type classification and will adopt a multimodal approach to incorporate various types of data into the learning process.

ACKNOWLEGEMENTS

This research was supported by the "Research of Construction Codes Library and Ontology for Digital Transformation of Construction Codes" project, part of the "Research on the Development of Construction Standards Operated by the Korea Construction Standards Center" project of the Korea Institute of Construction Technology (KICT).

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