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RULE-BASED INFERENCING DIAGNOSIS IN HBIM

1. Introduction

In refurbishment and restoration, the understanding of damages involves complex tasks that require the integration and interpretation of information acquired in a multidisciplinary manner, which is an ability of Historic Building Information Modelling (HBIM) (López *et al.* 2018). The risk management and mitigation depends on the certainty of diagnostic results, which constitute a knowledge system, able to assist professionals through a guided decisional process (Ottaviano *et al.* 2018). The scientific community agrees on the potentiality of HBIM for structuring information systems, in order to obtain a rationalized and coordinated management of the diagnostic phase (Murphy *et al.* 2013; Garagnani *et al.* 2016; Cera 2017; Bruno *et al.* 2018; Jordan-Palomar *et al.* 2018).

In recent years, HBIM approach is emerging as the most efficient methodology for the conservation of artefacts, thanks to the combination of volumetric and physical characteristics of a building, with all its constructive elements (Bruno *et al.* 2019), and the data management and analysis via relational databases, with customizable parameters and connections between elements (Dore *et al.* 2012). Indeed, HBIM enables the inclusion of several aspects of a heritage building in a BIM model, like information about materials or geometrical shapes, construction systems of various historic periods, with the aim of increasing the effectiveness of the preservation process. Moreover, HBIM supports the insertion of retroactive information for the development of restoration and management phases and it allows the establishment of preventive maintenance, through the exchange of data and the spreading of knowledge about the tangible cultural heritage (Bruno *et al.* 2018).

However, there are still not solid and shareable HBIM procedures about survey, geometric modelling and information and data management. Furthermore, the use of a multidisciplinary and interoperable platform does not guarantee an optimization of the decision process, because each phase and discipline are responsible for a peculiar thematic of the historical heritage preservation. Hence, there is a need for different tools for information exchange and integration.

The diagnosis consists both of quantitative analyses and qualitative assessments: the former, based on the results of investigations; the latter, influenced by the skills and experience of the experts involved. Artificial Intelligence (AI) could play an important role in the rationalization of the decision process, establishing priorities in conservation actions, according to the damage severity and the financial resources (Chávez-Hernández *et al.* 2012; Zhong *et al.* 2019). In literature, there are some applications of AI, for the optimization of procedures and techniques (Bloch, Sacks 2018; Juszczyk 2018). Nevertheless, one of the main gaps in knowledge is the use of AI within HBIM for decision-making automation. For example, decision trees (J48 algorithms) could serve for the conservation management of a pile panel (Bienvenido-Huertas *et al.* 2019). Also, machine learning applied to reality capture and data processing could provide a strategy for monitoring the defect evolution on masonry walls of historic buildings (Valero *et al.* 2018).

BIM-oriented information systems could formulate a diagnosis through the automatic computation of data retrieved from different sources, such as analysis of former transformations, visual inspection, image processing, diagnostic tests, monitoring, etc. (Nisheva-Pavlova *et al.* 2008; Bruno *et al.* 2018; Bienvenido-Huertas *et al.* 2019; Galantucci, Fatiguso 2019) Open-source toolkits for programming customized algorithms make BIM tools flexible, through the implementation of plug-in/add-ons or web-based software (Afsari *et al.* 2017). In this context, the research work proposes a workflow based on the use of inferential logic in the diagnosis of building decay for the management and computation of information, in order to identify appropriate interventions. The inferential logic may be defined by production rules, which convert engineers/architects expertise and literature background into a knowledge representation model expressing the "causes/effects" mechanism (Deng *et al.* 2017; Sousa *et al.* 2018).

The methodological framework is structured in the following phases: a) Geometric survey, after a preliminary knowledge acquisition; b) BIM and data modelling; c) Inference logics. It was tested on a masonry building: Masseria Don Cataldo, Bari (Southern Italy).

2. Methodology

2.1 *Geometric survey*

The implementation of a HBIM approach goes through a preliminary knowledge acquisition about the historic building via initial geometric survey, materials/construction analysis and typological studies (based on historical and photographic records, archival documentation and prior available drawings). This knowledge is valuable for planning further systematic investigations, including digital and three-dimensional geometric survey. Reverse engineering produces high-resolution 3D models in the form of point clouds or texturized polygonal meshes, even in case of complex and large-scale artefacts. Photogrammetry and 3D laser scanning are the principal methods for digital geometric surveys.

As far as the acquisition phase is concerned, the photogrammetric technique tends to be preferred, because of the broadly available and cost-effective equipment (compact, bridges or reflex cameras, tripods or telescopic rods, drones). The order of magnitude of the elements to be detected depends on the resolution and the complexity of the models. In photogrammetry, for example, given the noticeable influence of the scanning parameters (type of camera and lenses, focal length, shooting distance, overlapping between images, number of images, etc.) on the final resolution of the models, it is necessary to identify *a priori* the purpose of the investigation, in order to adapt the setup of the campaigns.

Once the image capturing is completed, the photogrammetric pipeline can start with the importation of the acquired image data into 3D reconstruction software tools like Agisoft Photoscan (Version 0.9.0: http://www.agisoft.ru/). Images are transformed by the collinearity equations, for removing distortions related to intrinsic parameters of the adopted camera (interior orientation). According to Structure from Motion, 3D spatial coordinates of each point on the object can be found out from the 2D images, by the identification of reciprocal position of cameras reproducing the same object points (tie points). This corresponds to the process of photo alignment and optimization. The sparse cloud (made of tie points) should be firstly orientated and scaled, by using some reference points of known coordinates and, then, refined by removing points affected by reconstruction uncertainty (reproduced in less than two photos) or by a substantial reprojection error (*Historic England* 2017). Afterwards, it is possible to reconstruct a dense point cloud with a resolution, which can vary according to the parameters setup (Agisoft LLC 2016).

2.2 *BIM and data modelling*

The BIM modelling is carried out by means of two practices: manual procedures and semi-automatic ones, using segmented point clouds (Point-to-BIM/Scan-to-BIM process). The point clouds, exported as .pts file, are linked in Revit Autodesk, after indexing the raw format in a Revit compatible one (.rcp). In the first approach, architectural elements are created by Boolean operations or by surface and solid-based objects, from original drawings or tracing manually primitive lines retrieved from point clouds (Lòpez *et al.* 2017).

Instead, the semi-automatic procedure generates parametric objects from the point clouds, using BIM libraries and customized commands for modelling and detailing BIM elements; in addition, an embedded tool evaluates the level of accuracy of the BIM model against 3D point data (FARO As-Built for Revit), according to USIBD standards (USIBD 2016). The software tool works finding the best-fitting lines within the point cloud data. The HBIM model is semantically enriched with information and data about the state of conservation and material/constructive features, as a result of the historical analysis of transformations, visual inspection, non-destructive diagnostic tests and simulations. The parametric modelling of decay mapping can be executed within the BIM environment, in 2D views, tracing bi-dimensional lines and regions. Thus, classifying and modelling each phenomenon allow the insertion of semantic attributes in the parametric object. Data modelling of parameters follows the principles of rule-based inference logic for automating the diagnosis.

2.3 *Inference logics*

The inference logics generally include three parts: a) a knowledge base that is a set of production rules; b) a global database or working memory; c) an inference engine. A production rule consists of an IF part (or premises, antecedent part) and a THEN part (or consequent part). The premises are collected by IF and linked to each other through logical connectives (and/or); instead, THEN introduces one or more actions or conclusions to be performed when the premises are true. Each rule belongs to a chain of rules and generates a knowledge base. The global database is the BIM database of parameters in each damage pattern object. The inference engine consists of: the pre-diagnosis, with the first series of surveys and tests, and the damage patterns identification (Step 1 and Step 2); the diagnosis of the possible causes (Cn), supported by further surveys and tests for reducing the level of uncertainty about actual causes (ACn) (Step 3, Step 4 and Step 5); and the suggestion of coherent interventions (In), after achieving a sufficiently high confidence factor (Step 6) (Fig. 1).

The inference mechanism or the control strategy can be of two typologies: backward chaining and forward chaining (Adeli 1988). Backward chaining is a logical process to identify the actual causes starting from highlighted symptoms; instead, forward chaining finds the connection between actual causes and appropriate interventions. The scope of the inference engine is to verify if the hypothesis, suggested by the visually inspected decay pattern (DP), is confirmed. In this case, the inclusive disjunction (OR) are used, because a conclusion is true if and only if one or more of the evidences are true.

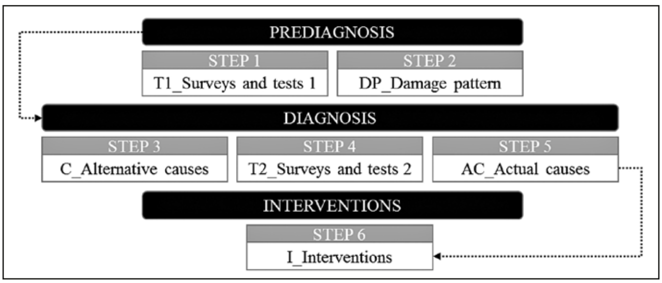

Fig. 1 – Inference logic framework.

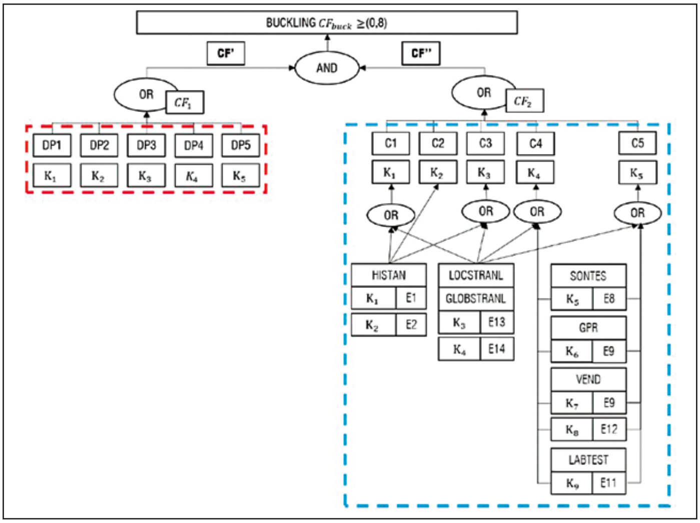

Fig. 2 – Inferential tree for buckling: pre-diagnosis (red), diagnosis (blue).

According to the rule-based inference logic, the knowledge representation should consider the uncertainty (Fig. 2):

R1: IF "DP1 (K1) ∨ DP2 (K2) ∨ DP3 (K3) ∨ DP (K4) ∨ DP5 (K5) are observed" THEN "The settling is Buckling (CF1)" (1)

where:

– DP1 (multiple vertical cracks on continuous wall); DP2 (Vertical cracks with direct hyperbolic shape on isolated wall); DP3 (Vertical cracks with direct hyperbolic breaking surface on pillars/columns); DP4 (Splitting of parts of stones/mortar on the corners at the bottom in pillars and walls); DP5 (Wall section partialization);
– Kn the confidence threshold of evidences;
– CF1 the certainty factor of the rule R1.

The final CF of the conclusion H is given by the formula:

$$CF'(H)=max\ (K1, K2, K3, K4, K5)\ x\ CF1 \tag{2}$$

because the evidences are related with the OR operator.

The diagnosis phase requires programmed surveys and tests (T2). Operators are not completely conscious about the correlation between the single test result and the actual causes. The awareness could increase with the integration of other data and information:

R2: IF "E1 ∨ E2 ∨ … ∨ En"
THEN "The possible causes are C1, C2, …, Cn"

R3: IF "C1 (K1) ∨ C2 (K2) ∨ C3 (K3) ∨ C4 (K4) ∨ C5 (K5)"
THEN "The settling is Buckling (CF2)"
CF"(H)=max(K1, K2, K3, K4, K5) x CF2

(3)

where En are the evidences, i.e. the results of survey and tests (Tab. 1). The certainty factor $CF_{settling}$ of the final hypothesis is the combination of the confidence factor CF1 and CF2 of the two rules R1 and R3, as:

$$CF_{settling} = \begin{cases} CF' + CF'' - CF'CF'' & CF', CF'' \geq 0 \\ CF' + CF'' + CF'CF'' & CF', CF'' < 0 \\ \dfrac{CF' + CF''}{1 - min\{|CF'|, |CF''|\}} & otherwise \end{cases}$$

AND "The causes are C1 ∨ C2 ∨ C3 ∨ C4 ∨ C5"

(4)

T1_Survey and tests 1		
CODE	**DESCRIPTION**	**RELATED EVIDENCE**
HISTAN	Historical analysis of transformations	**E1**_Identification of interventions on structures and building component **E2**_Identification of changes in destination of use **E3**_Disasters (earthquake, explosion, fire, war attacks, etc.)
MORPAD	Mortar pads	**E4**_Monitoring and measurements of cracks parameters (length, width, depth, direction of propagation, extension) **E5**_Monitoring and verification of speed of crack progression **E6**_Analysis of stone bricks and mortar joints to identify constructive regularity and quality
STRGAU	Strain gauges	
IMAGEDET	Crack detection with image processing	
MESHDET	Crack detection with mesh processing	
DEFMET	Deformometer	**E7**_Presence of deformation (for compression and bending strains)
T2_Survey and tests 2		
SONTES	Sonic tests	**E8**_Estimation of propagation speed of mechanical waves to identify the quality of masonry, before and after consolidation
GPR	Ground Penetrating Radar	**E9**_Presence of internal cavities, cracks, discontinuities (E9)
BOREHOL	Drilling borehole	**E10**_Destructive test, to be punctual to analyse the borehole and the exported coring sample and identify the component stratigraphy (E10)
LABTEST	Laboratory tests	**E11**_Laboratory tests to estimate mechanical parameters and physical/chemical compounds (E11)
VEND	Endoscopy	**E12**_Identification of stratigraphy (material aspect and thickness) E9_Presence of cavities, cracks
LOCSTRAN	Structural analysis – local behaviour (with current regulations)	**E13**_Compression strains higher than failure compression strains in pillars, column, walls (computation with current regulations)
GLOSTRAN	Structural analysis – global behaviour (with current regulations)	**E14**_Effects on the overall building; analysis of the alternatives of intervention (computation with current regulations)

Tab. 1 – Data model of survey and tests.

Once the causes are established, the wizard suggests the interventions (In) to eliminate the causes of settlings and to improve the mechanical behaviour of the masonry. The values of the confidence threshold Kn and the certainty factor CFn are defined by the experts involved in the diagnostic process. The user may select the BIM object representing the damage pattern and the related shared parameters (*.txt). Indeed, the surveyor chooses, among pre-compiled shared parameters sheets, the one about the presumed settling.

The inferential system is implemented in a Dynamo Studio Autodesk script via Visual Programming Language (VPL). VPL is a modular programming language consisting of a graphical notation with visual signs and rules, in form of nodes, for easy and flexible scripting with and without textual snippets. Initially, these tools were employed for 3D parametric modelling, but further developments have been enhancing features for data analysis and management. There are several data format that could be analysed (coordinates, numbers, text, images, meshes and point clouds). VPL has the capability to represent rules in a machine and human-readable language. The use of networked nodes provides readability and flexibility of programming flowcharts. It also creates a bi-directional link with the BIM objects for real-time geometric and semantic modifications (Tab. 1).

3. Discussion

The pilot case is Masseria Don Cataldo (Bari, Southern Italy), a noble farmhouse, whose original nucleus was made up of a small two-story building, dated back to 1719 (Stangarone n.d.) and surrounded by boundary walls, enclosing a small private chapel. The building has been abandoned since the early XX century, and it is subjected to widespread degradation. The image capturing phase was carried out on the 14 September 2016, within a MIUR Start-up project[1]. The scans covered the whole external area of the masonry building and the octagonal central hall, decorated by tempera frescos on the mirror vault. For the three main façades, a Parrot Bebop drone was used, with a 14 Megapixel camera sensor, and wide-angle lenses, with a focal length of 1.83 mm. The acquisitions of 935 images were realized at a flying distance of 4 m from the masonry surfaces and a flight speed of about 0.3 m/s. Instead for the internal central hall, the scans were executed with a mirrorless camera, Samsung NX 2000, with wide-angle lenses at a fixed focal length of 16 mm. The camera was mounted on a carbon fiber telescopic rod, so that a sufficient overlapping between images was reached. In this case the shooting distance was of 5.2 m, with 166 images.

The dense point cloud of the external area is made of 28 million points (Ground Sample Distance of 2.3 mm/pixel in the 3D model), with medium quality and an aggressive depth filtering; while, the dense cloud of the central

[1] Polishape 3D srl, Politecnico di Bari, Building Refurbishment and Diagnostics srl, Università degli Studi di Napoli Federico II, *Progetto PAC02L2_00101 "Sistema senza Contatto per la Diagnostica con Realtà Aumentata di Manufatti di Rilevante Interesse Culturale e di Difficile Accessibilità" (Documento di lavoro)*, Bari-Napoli, 2013.

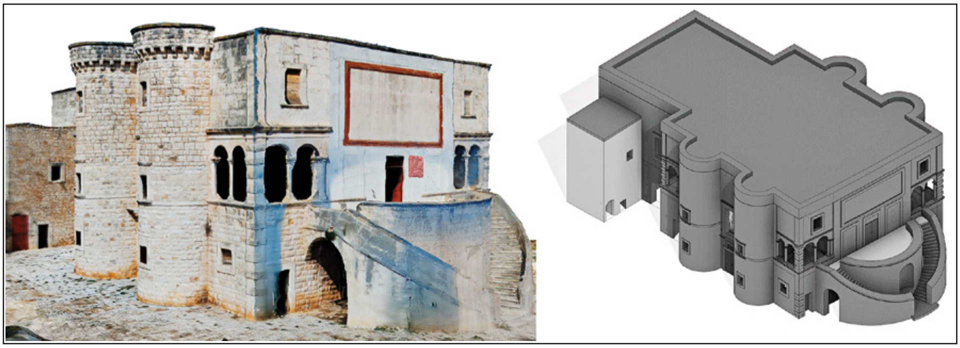

Fig. 3 – Texturized polygonal mesh and HBIM model.

hall is of 35 million points (GSD of 1.12 mm/pixel). The following step concerns the creation of polygonal meshes and textures. The obtained meshes are of 11 million faces for the whole building, and of 7 million faces for the hall. The BIM model was obtained by a manual procedure applied to vaults and openings of the whole structure; while, for the "salone ottagonale" the semi-automatic tool was tested on walls and openings (As-built for Revit plug-in) (Fig. 3).

Actually, the plug-in does not recognize automatically walls, windows and openings, but it calculates the best fitting primitives compared to the point cloud, after the manual selection of two or four points. The selection of family type is still user-defined. The automation lies in the recognition of the thickness of walls, openings and windows when modelling them. The deviation analysis was conducted evaluating the percentile of points with $\varepsilon <$ 30 mm, according to the USIBD specification (USIBD 2016). The error and the scale representation suitable for surveying historic and cultural heritage buildings are respectively 2-3 cm and 1:50. An acceptable error of maximum 3 cm is fixed, considering tolerances and possible divergences caused by the construction features and decay conditions. The percentage of 95% for LOA 500 was not achieved, also because the deviation analysis did not count the out of plumb of walls, the areas of plaster splitting, and other superficial irregularities.

Inference logic was implemented on the case study: the testbed of the inference engine confirmed the buckling hypothesis. The buckling can be caused by different phenomena, such as structural load increase, reduction of bearing section, alteration of load distribution on bearing wall, ageing of materials (mortar decay), low constructive regularity and quality (presence of stone bricks and thick mortar joints with low mechanical characteristics).

Visual inspections and preliminary historical analysis of former transformations revealed the presence of multiple vertical cracks on a continuous

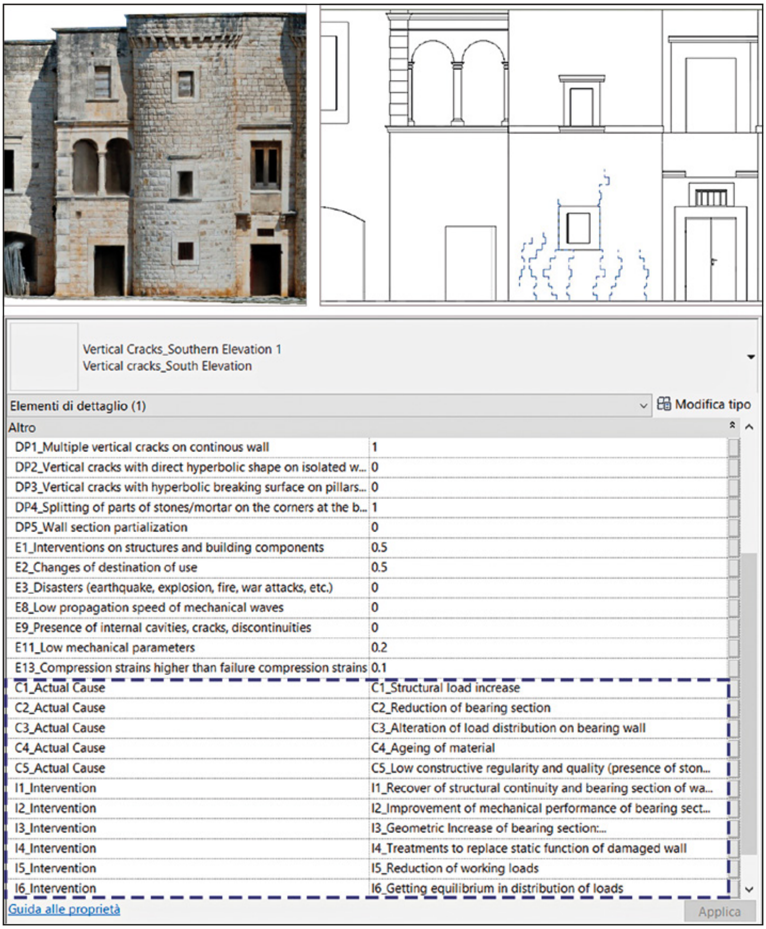

Fig. 4 – BIM object about crack pattern and automatic updating of parameters.

wall (DP1), covering the entire height of the ground floor of the towers and galleries (South elevation). The cracks cross the mortar joints and stone bricks, with splitting of parts of material, and there is an evident status of aging of incoherent materials (mortar). In addition, the basement of the towers is affected by overloading caused by the subsequent construction of the upper floors, as evident from the diverse material of stone blocks, and from the masonry textures.

Before the implementation of the script, the object representing the decay pattern (multiple vertical cracks) was semantically enriched with shared parameters, defining the data type as numbers and multiline text (Tab. 2).

Parameter	Variation range of confidence threshold (Kn)	Assigned confidence threshold (Kn)
DP1_Multiple vertical cracks on continuous wall	0/1 (NO/YES)	1=YES
DP2_Vertical cracks with direct hyperbolic shape on isolated wall	0/1 (NO/YES)	0=NO
DP3_Vertical cracks with hyperbolic breaking surface on pillars/columns	0/1 (NO/YES)	0=NO
DP4_Splitting of parts of stones/mortar on the corners at the bottom in pillars and walls	0/1 (NO/YES)	1=YES
DP5_ Transversal reduction of bearing section	0/1 (NO/YES)	0=NO
E1_Interventions on structures and building components	0-1	0.5
E2_Changes of destination of use	0-1	0.5
E3_Disasters (earthquake, explosion, fire, war attacks, etc.)	0-1	0
E8_Low propagation speed of mechanical waves	0-1	0
E9_Presence of internal cavities, cracks, discontinuities	0-1	0
E11_Low mechanical parameters	0-1	0.2
E13_Compression strains higher than failure compression strains	0-1	0.1

Tab. 2 – Shared parameters about symptoms, surveys, actual causes and interventions.

The values in the third column correspond to the confidence threshold (Kn) assigned by professionals to each evidence involved in the rules, in the BIM object.

After selecting the object related to the decay pattern (multiple vertical crack), the engine extracted parameter values useful to detect the actual causes and the coherent interventions (In), which are automatically updated (Fig. 4).

4. Conclusion

The contribution pertains to the implementation of a methodological framework, which employs geometric/information modelling and data management, within the HBIM approach, for automating the diagnosis of decay. In particular, the automation is assisted by ruled-based inferential logic, structured in Visual Programming Language. An advantage of using BIM lies in the flexibility of computing data previously structured in the HBIM model. The additional benefit is the interoperability of files, retrieved from survey data, within BIM tools, for their parametric conversion into BIM objects. In particular, the employment of manual procedures for designing irregular shapes of vaults is required, because of the limits of automatic modelling.

The accuracy obtained for walls and openings of the main room is sufficiently high, considering the tolerances and divergences caused by the construction features and decay conditions. Moreover, the point cloud linked to the HBIM model has an adequate resolution to represent masonry textures and decorations, and to document the state of conservation. The experimentation demonstrates that the rule-based inferencing diagnosis is a guided process, which increases the factor of certainty about settlings and actual causes, on the basis of surveyors' technical insights and evidences. Finally, it suggests appropriate intervention measures. Future remarks will involve the use of machine learning within the pre-diagnostic procedures, in order to automatize the object recognition and labelling, and enhance the detection of decay patterns, starting from the application of digital image processing techniques. It would be interesting also to introduce artificial intelligence, in the phase of assignment of confidence thresholds to the evidences. The methodology could be also applied to assess the state of decay of existing infrastructures (railways, bridges, airport structures) for diagnosing causes and identifying measures avoiding additional risks.

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ABSTRACT

The aim of this paper is the implementation of a methodological workflow for the diagnosis of masonry settlings, within the HBIM approach, developing a rule-based logical inference tool in Visual Programming Language. The rule-based inferencing diagnosis is a guided process, which increases the confidence factor about settlings and actual causes, on the basis of surveyors' technical insights and evidences. The final step is the suggestion of appropriate interventions. The results show that inference logic is directly applicable to the diagnosis problem; their efficacy depends on i) the structured parametric and data modelling of decay patterns in the HBIM model and ii) the knowledge base training. The application has been validated on a case study, Masseria Don Cataldo (Bari, South Italy).