Detection of Steel Structures Degradation through a UAVs and Artificial Intelligence Automated System

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Abstract: - In recent times, the need for the management and monitoring of steel structures (bridges, but also buildings) has become more and more important; consequently, a new phase has opened up aimed at the surveillance and monitoring of these structural types with the objective of their protection and preservation, also through preventive maintenance activities. Leaving aside the world of large structures (industrial buildings, bridges, etc.), the reality of metal-framed buildings in Italy is not yet strongly established. For this reason, particular attention must be paid to these types of structures. The application of experimental monitoring techniques, however, involves the succession and chaining of various established procedures. Visual inspection is generally the first step to assess any deterioration, but it becomes quite difficult for elements at significant heights. The operational difficulties can be reduced by the UAV drone. Image processing using soft computing techniques also offers the possibility of speeding up the inspection by human operators, who can limit themselves to assessing any damaged parts already selected by artificial intelligence. It is, therefore, necessary to establish appropriate automatic or semi-automatic inspection procedures mainly aimed at providing useful indications to operators on intervention priorities. An automatic monitoring and management procedure is therefore presented, which provides for the detection and evolution of degradation on structural elements and joints of existing steel structures. The implemented methodology follows five main phases: (a) images acquisition by UAVs; (b) 3D creation with geometry and degradation; (c) data processing and defect detection; (d) creation of an "evolutionary" database, able to update the degradation on the basis of the acquisitions made in subsequent inspections by UAVs; (v) implementation of the structure (with its defects) within a structural analysis software FEM (Finite Element Method).

Key-Words: - Computational Intelligence Systems, Soft Computing, Dynamical Systems, Management and surveillance.

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1 Introduction

The global transport infrastructure system and in particular the Italian one is obsolete. The Italian Ministry of Infrastructure has given a great impetus towards the monitoring of the road system in general with reference to both seismic aspects, landslide movements and flood aspects. In recent years, there has been a series of instability and collapses that affect transport networks in general, causing damage to the community and endangering the safety of users. For this reason, the Italian Ministry of Infrastructure started a series of studies and research activities related to road safety; in particular, in 2020 guidelines were issued concerning the monitoring of transport infrastructures from a structural/geotechnical/hydraulic point of view. For this reason, there is a growing demand for better monitoring of the condition of transport infrastructure worldwide. Bridges are key components of transport infrastructure and require such monitoring. In Europe, most road infrastructures were built from 1945 to 1965, in the post-war period. The load conditions of the bridges have recently changed due to increasing transport volumes and vehicle sizes. In addition, most of these bridges are subject to gradual deterioration over time and many are now structurally deficient, [1], [2]. Rehabilitation and life extension of these structures raise important maintenance and safety issues. However, an increase in bridge inspections to address existing structurally deficient bridges has considerable costs and practical implications for road owners and managers.

Automated monitoring of structures plays a key role in the digitization of our infrastructure, [3], [4].

Bridges, in particular, are increasingly equipped with measurement technology so that their condition can be permanently monitored. With reference to newly built bridges, static and dynamic monitoring techniques are already proceeding with [5]. The inclusion of monitoring systems that provide useful indications on the evolution of infrastructures [6], in predictive maintenance, such measurement data are used to initiate maintenance procedures at an early stage to avoid bridge closures. The difficulty is to evaluate the data in such a way that bridge conditions are calculated automatically. Machine Learning (ML) methods can be useful in this evaluation.

The difficulty lies in applying the developed ML methods to actual measured data in practice and generating added value for the owners and operators of bridge structures, [7], [8], [9]. Bridge monitoring systems generate large amounts of data. A manual evaluation is often unrealistic or only to a limited extent.

Steel bridges usually have high-strength bolt connections for the assembly of the load-bearing elements of the structure. However, these bridges are often used in adverse environments and are subject to corrosion, vibration and fatigue, and thermal cycling, which can contribute to bolt damage, [10]. Due to the enormous energy released by brittle fracture, fractured bolts will fail. Damage to the bolts will threaten the safety of bridges and may even lead to serious accidents. Therefore, it is necessary to monitor the condition of the bolt during daily operation and maintenance.

In the last years, computer vision technology has gained considerable attention as an interdisciplinary subject and has been used in monitoring and inspection activities of civil infrastructure to enhance the efficiency and accuracy of manual visual inspection.

A quasi-automatic bolt looseness detection method was proposed by Huynh et al, [11], in which plausible bolts were detected using a CNN-based object detector and the rotation angle of each bolt was measured by the Hough line transform. A method for measuring the angle of rotation of bolt slack using a CNN-based object detector was proposed by Zhao et al., [12]. A computer vision-based method integrating perspective transformation to detect bolt looseness for flange connections was designed by Wang et al., [13]. However, there is no automated procedure for all these works.

In this study, we focus mainly on the data acquisition methodology and the type of monitoring tested, focusing on the detection of deterioration in bolted plates using neural networks.

2 Materials and Methods

2.1 Methodology

Bolted joints are very common and important in engineering structures, [14], [15], [16]. Due to the extreme service environment and load factors, bolts often become loose or even slackened. Detecting loose or disengaged bolts in real time or in a timely manner is an urgent necessity in practical engineering, that is crucial for maintaining structural safety and durability, [10]. Recently, a lot of machine learning and deep learning techniques and methods to detect bolt loosening have been proposed. However, in most of these studies, images of bolts captured in the laboratory are used for model training. The images are acquired under well-controlled light, distance and viewing angle conditions. It should be noted that in practical engineering, the above-mentioned well-controlled laboratory conditions are not easy to realize, and images of real bolts often have blurred edges, oblique perspective, partial occlusion and indistinguishable colors, etc., which cause trained models obtained under laboratory conditions to lose their accuracy or falsify.

The proposed system is developed in 4 main phases, according to the flowchart in the figure (see Fig. 1).

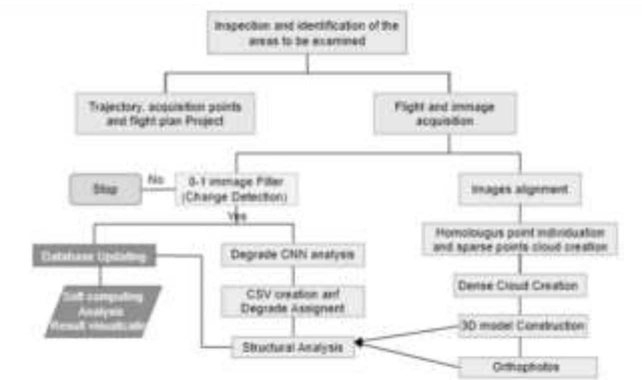


Fig. 1: Flowchart of the proposed methodology.

- Preliminary phase:
    - survey and identification of areas to be examined: necessary step to assess the presence of any obstacles that the drone may encounter and definition of points of interest;
- Flight:
    - Design of the flight plan and acquisition: necessary step to define the flight trajectory (way point), the acquisition spatial intervals (choice of image acquisition positions), the

inclination and rotation angle of the camera, the travel speed, the duration of the mission;
- Flight and image acquisition: the drone automatically flies along the planned trajectory and acquires the images needed for 3D modelling, orthophoto generation, degradation detection;

- Processing:
  - Reconstruction of 3D model and high-resolution orthophotos (orthomosaic)
  - Detection of deterioration via CNN
  - Deterioration image processing assignment;
  - Visualisation of deterioration on ortho-mosaic model;
  - Structural analysis of infrastructure for different deterioration scenarios;
- Visualisation of results
  - Creation of a historical database of points of interest;
  - Querying the database of overlapping layers.

The objective of using drones and planning flight plans is to allow the end user to always be able to acquire images from the same position and at the same angle conditions (using cameras with the same characteristics), which is necessary to avoid pre-processing rectification.

On the other hand, the goal of Machine Learning is to extract knowledge or information and correlations from these data.

A dataset for the detection of 'bolt' objects in natural scene images was developed by implementing it with datasets freely available on the web, [17]. In this application, the reference categories applied to object detection are two "head" and "nut".

Advanced object detection models (such as YOLO v5) were used for testing the dataset. The evaluation results show that the bolt target detection model trained using this dataset can detect and classify the bolt head and bolt nut well in the natural environment. In the YOLO v5-l model, the average accuracy of the two main categories reaches 97.38% and 91.88% respectively. The proposed dataset bridges the gap in the current field of bolt object detection.

3 Case Study

The operations were tested on a low-traffic road in the territory of the town of Cardeto (RC), Southern Italy, in an area with low density and traffic. It is an interurban road infrastructure that connects the city center with a village that runs along the bank of a river (Fig. 2).

Fig. 2: Bridge case study.

In order to determine the trajectory of the UAV, it is first necessary to provide an initial inspection to avoid interference with any obstacles during data acquisition, to prepare the take-off and/or landing point and data transmission, to verify the possible presence of overflying areas subject to vehicular or pedestrian traffic, and then to provide for the installation of all appropriate 'precautionary' measures to mitigate the danger (parachutes, control cables, etc.).

Having determined the space of the trajectory and the points of interest for the inspection (areas to be acquired), the information was transposed using a flight planner and then the trajectory was drawn, and the take-off-landing/data transmission and image acquisition points were determined (Fig. 3).

Fig. 3: Automated flight plan.

This provides repeatability of the flight and images (with the same camera used) that can be easily compared, especially in terms of changes in the structure (presence of degradation, improvement interventions, etc.).

Once the data and information necessary for analyzing the bridge had been acquired, the various phases of data processing were conducted. The images were processed using the Metashape software and the digital 3D model was reconstructed from which the geometric characteristics were extracted. In addition, orthophotos were produced, in which the various processing steps performed on the individual frames can be reported.

Subsequently, individual frames were processed through the proposed model in order to identify individual bolts. Image processing follows these steps image acquisition; (2) pre-processing; (3) processing; and (4) detection of deterioration, [15]. Recently, deterioration detection methods based on deep learning have been proposed, [16]. CNN has disadvantages such as a high computation cost and a long operation time. However, the reduction of the areas to be inspected within a single frame allows significant regions of the infrastructure to be scanned more quickly, [17], [18]. Once the different frames have been acquired, masks have been designed, which allows the processing time of acquisitions made at later times to be significantly reduced.

In Fig.4 a Flow Chart explaining the image processing system for detecting the deterioration [19] [20], [21].

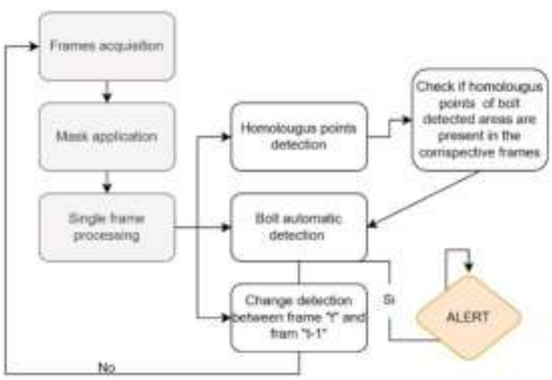
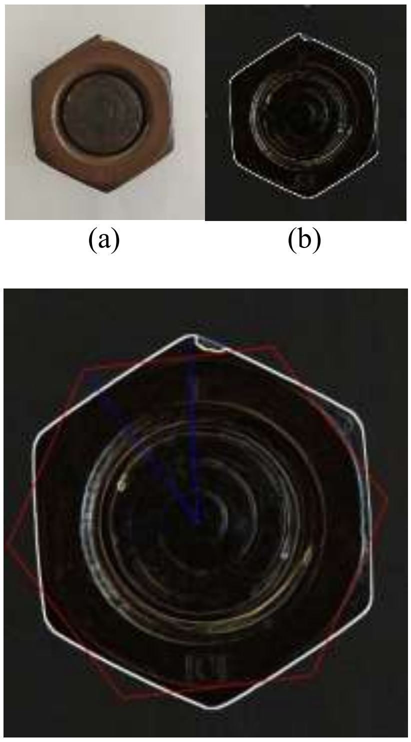


Fig. 4: Explanatory Flow Chart of the deterioration image processing system

Fig. 5 shows an example of a bolt loosening evaluation. The frame acquired at instant *t* (Fig. 5a) is processed through an edge detection algorithm to enhance its contours (Fig. 5b) and facilitate comparison with the frame acquired and processed at instant *t+1* (Fig. 5c). The acquisition of frames at different instants through the use of UAVs facilitates this comparison operation, having designed through a flight planner the acquisition points while maintaining constant distance and camera angle.



(a) (b)

(c)

Fig. 5: An example of a bolt loosening evaluation.

Fig.6a shows the results of processing a single frame where all present bolts are recognized through YOLO v5. Fig. 6b shows the processing of a frame in which only the bolts present in certain areas are recognized. The processing of such frames is sufficient for the identification of the deteriorations (slippages and breaks) through the comparison with the frames acquired in subsequent shots. The same frames are also used through the use of homologous points for the identification of the same bolts on overlapping portions of frames where processing has failed (Fig.7).

(a)

(b)

Fig. 6: a) locating bolt heads on deck b) locating bolt heads on the pier.

Fig.7 shows an example where bolts belonging to the same area are not recognised by the algorithm and therefore require further processing for comparison with frames showing the same areas where, however, all bolts have been recognised.

Fig. 7: Zoom on an area with processing problems - red arrows indicate bolts not recognised by the processing system.

The proposed system also consists of a system for visualizing the results, which makes it possible to compare the evolution over time of the variations occurring on the bridge. Given the repeatability of the flight plan, the images acquired from a given position will frame the same areas and thus be easily comparable, creating a temporal database. This information available on the visualization platform helps and enables the operator to 'visually process' the changes.

In particular, a filter (0-1) will then cause the image itself to be added to the database whenever a change from the previous temporal acquisition is detected. Changes in degradation, depending on the point of acquisition, will be associated with a particular element (waypoint determined in the preliminary phase) and recorded on a CSV file. The acquisition data and analysis results can then be made available within a user-questionable platform, making the results accessible to end-users for prioritized action considerations.

4 Conclusion

As is well known, Italy's building and infrastructure heritage suffer from significant problems related to the age of construction., the state of maintenance and the particular vulnerabilities due to the adoption of construction techniques that are not always adequate with respect to the possible load conditions.

The antiquity of Italy's infrastructure network and the absence of a reference database for planning the maintenance work the infrastructure network needs is one of the most widespread problems in our country. As bridges become obsolete, inspection and maintenance requirements increase [22-23]. In this work, in accordance with the new guidelines on Risk Classification and Risk Management and Safety Assessment and Monitoring of Existing Bridges, a new methodology is proposed to establish an appropriate inspection procedure and intervention priorities. Traditionally, bridge maintenance has been based on visual inspection methods that are highly variable and lack resolution and can only detect damage when it is visible. Therefore, structurally deficient bridges can be left undiscovered. A number of bridge collapses have occurred due to a lack of information on structural capacity and it is therefore clear that visual inspection alone may not be adequate for monitoring the condition of bridges. In countries such as Japan, which is prone to natural disasters, it is recommended that monitoring of engineering infrastructure such as bridges be conducted continuously.

Monitoring and structural diagnostics are particularly topical issues as techniques that can be usefully adopted for safety assessment and more generally for the proper management of existing constructions. In fact, monitoring overlaps with structural diagnostics activities with the aim of checking the behavior of constructions over time, with longer observation periods, even of several years, aimed at controlling the evolution of certain aspects of interest, such as, for example, the presence of some structural damage or form of degradation, or the existence and entity of cracking frameworks. By verifying their possible evolution over time, monitoring provides overall feedback with which to ascertain the change in structural characteristics, which may be indicative of a significant increase in structural damage.

With reference to a case study, an experimental and automated methodology capable of acquiring geometric information and the state of degradation of a bridge in Cardeto was presented.

This information, available on the visualization platform, helps and enables the Authority to determine the priority of maintenance interventions.

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