Building surface damage recognition based on synthetic data

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***Abstract*—To detect surface damage to buildings, it is necessary to involve workers who are at risk of industrial injuries when inspecting hard-to-reach areas of industrial premises. Attraction of special means, such as aerial platforms, safety systems, etc. increase the financial costs with this approach. The use of unmanned aerial vehicles, coupled with neural network algorithms, can simplify this procedure. Due to the inaccessibility, the problem of obtaining training data for neural networks arises, which can be solved by synthesizing them in a virtual environment.**

Keywords—damage modeling, cracks, synthetic data, convolutional neural networks

I. Introduction

Enterprises with numerous of infrastructure facilities need operational monitoring of the state of each of the facilities for more efficient management and prevention of undesirable risks. This can be caused primarily by legal and regulatory requirements for stability and security, as well as an increase in the competitiveness of the organization [1]. Until recently, visual inspection has remained the main method for detecting surface defects such as cracks, chips, and corrosion, however, certain limitations have motivated work on approaches to automatic crack detection [2, 3]. This is because conditions noted during periodic inspections may require more frequent inspections, which forces a focus on improving the efficiency, safety and accuracy of visual inspection. The problem also lies in the fact that this type of inspection is largely based on manual data collection with the naked eye, and some approaches require inspectors to access various hard-to-reach infrastructure components [4]. Thus, to ensure safety, for efficient and accurate inspection of infrastructure facilities, it is required to use an automated data collection system [5]. The unmanned system, which reduces the role of the inspector, provides a safer and more efficient control, because can fly to all parts of a large structure to collect data using cameras and sensors installed on it [6], and the automation of the UAV flight path leads to a collision-free path with minimum overlap, maximum coverage and minimum flight time [7].

The use of neural network algorithms makes it possible to automate the process of processing video data, reducing the workload on personnel and increasing the efficiency of damage monitoring. For the efficient operation of neural network algorithms, it is important to provide a large amount of data for training, the collection and labeling of which in the classical manual way, as a result, is expensive and problematic, especially for hard-to-reach infrastructure objects. Due to the complexity of obtaining a data set for training neural networks, it is possible to use synthetic data modeling technology [8]. The successful development of technologies for realistic rendering and visualization of three-dimensional data has made it possible to use development tools such as Unreal Engine and Unity to automatically create and collect data for training neural networks in applied problems of object detection and classification [9].

II. Defect Detection

The Res-UNet network [10] was used as a neural network classifier for the problem of defect detection. Data for training was prepared in 2 stages: in the first stage, control data was collected from video frames and photographs obtained during field surveys of real infrastructure facilities. These frames went through the stage of manual markup for a specific task, after which the image was divided into small fragments of 256x256 pixels. Training and validation sets were formed in a ratio of 9 to 1. Training was carried out until an accuracy of 95-98% was achieved on the validation set. The masks obtained on the test images went through the stage of blurring and thresholding to cut off false positives on individual pixels.

In the absence of the possibility of shooting real world scenes with the required damage, such as cracks and rust, at the second stage of data preparation, training samples were formed using simulated synthetic data in the Unreal Engine environment (Figure 1). The development environment made it possible to implement a pipeline for the automatic creation of synthetic defects by creating virtual scenes with various types of infrastructure research objects. Thus, a sample of the wall and roof was formed with customized materials with the imposition of procedural textures of defects on them for the final rendering [11]. Scanned real fractures from the public Quixel Megascans dataset (Figure 1) [12] were selected as the basis for generating fracture variations.

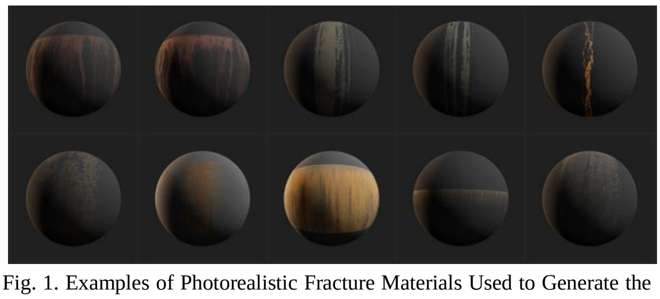

Fig. 1. Examples of Photorealistic Fracture Materials Used to Generate the Synthetic Training Dataset

Thus, to identify mechanical defects of surfaces and roofing, more than a thousand images were synthesized, copies of RGB images from which can be seen in Figure 2.

Fig. 2. Synthetic data modeled in Unreal Engine

The implemented data generation pipeline also allows you to automatically create defect masks for training neural network algorithms, an example of which is shown in Figure 3. As a result, the ability to create unlimited variations in the appearance of surfaces due to combinations of textures and point adjustment of the material of virtual objects makes virtual scene rendering a convenient tool for creating datasets , including data from any point of view of the object of study in the virtual scene.

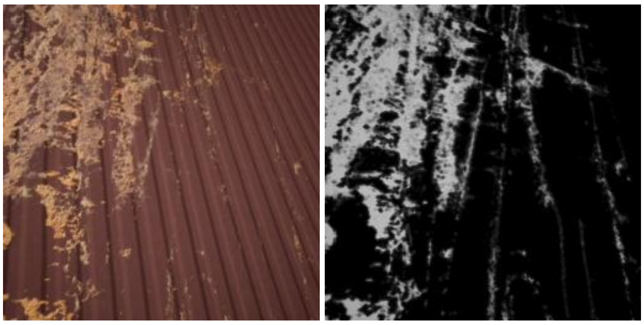

Fig. 3. An instance from an automatically generated synthetic dataset (rgb image of a rusted roof top (left) and defect mask (right))

III. Conclusion

The neural network algorithm was trained on the obtained synthetic data and showed high accuracy in detecting building surface integrity violations (Figure 4). As can be seen from the figures, the approach used makes it possible to train and recognize defects with minimal time and resource costs.

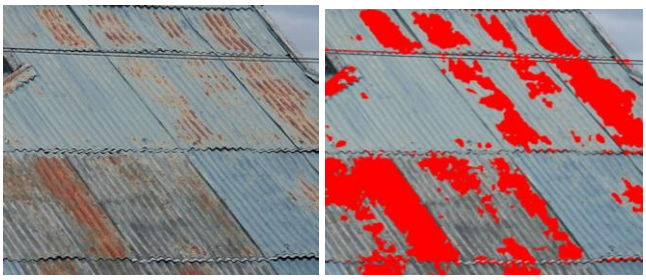

Fig. 4. Results of segmentation by a neural network algorithm

Based on the results of the study of control infrastructure facilities for the presence of defects, the following accuracy indicators of the neural network algorithm were obtained, the table 1 of the results of which is presented below:

TABLE I. PRECISION, RECALL AND F1 VALUES FOR RUST AND CRACK DETECTION IN THE CONTROL GROUP OF OBJECTS.

	Rust	Cracks
Precision	78%	91.3%
Recall	91.2%	87.1%
F1-score	84.1%	89.2%

Thus, the use of the approach for generating synthetic data of surface defects based on photorealistic rendering made it possible to ensure the accuracy of detecting the localization of cracks and rust on infrastructure facilities by 91.3 and 78%, respectively.

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