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Procedia Computer Science 170 (2020) 656–663

Procedia Computer Science

www.elsevier.com/locate/procedia

The 3rd International Conference on Emerging Data and Industry 4.0 (EDI40)
April 6-9, 2020, Warsaw, Poland

# Assessment and Use of Unmanned Aerial Vehicle for Civil Structural Health Monitoring

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**Abstract**

Unmanned Aerial Vehicles or UAVs can be employed in a multitude of civil applications owing to their ease of use, low maintenance, affordability, high-mobility, and ability to hover. Such vehicles are being utilized for real-time monitoring of road traffic, providing wireless coverage, remote sensing, search and rescue operations, delivery of goods, security and surveillance, precision agriculture, and civil infrastructure inspection. They are the next big revolution in technology and civil infrastructure is expected to dominate their more than $45 Billion worth market. This paper surveys the UAV assisted Structural Health Monitoring or SHM literature over the last decade and categorizes UAVs based on their aerodynamics. Further, it presents the payload product line to facilitate the SHM tasks, details the different applications of UAVs exploited in the last decade to support civil structures and discusses the key challenges faced in its application across various domains.



*Keywords:* Type your keywords here, separated by semicolons ;

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1877-0509 
10.1016/j.procs.2020.03.174

## 1. Introduction

UAV Assisted Structural Health Monitoring (UASHM) had emerged as a viable and promising option to overcome the challenges of both Visual Inspection, Wired Structural Health Monitoring (WSHM), and Wireless Structural Health Monitoring (WLSHM), especially for civil structures. An Unmanned Aerial Vehicle (UAV) is defined by the Federal Aviation Authority (FAA) as an aircraft flown with no pilot on board. UAVs are also referred to as drones, and the name can be used interchangeably. The vehicle is controlled either autonomously or with the use of remote control by a pilot from the ground and can carry a wide range of devices, including image, video, infrared, and other types of sensors [18]. UAVs are an emerging technology with many potential applications in civil engineering. A consistent concern in SHM of civil structures is efficiently and effectively visually inspecting a wide variety of structure types in challenging locations [1][3]. The UAV assisted SHM of Civil infrastructure is expected to dominate more than $45 billion market of UAVs due to its many advantages, a few of which are:

*Navigational Ease* — the deployment of the sensor varies from one structure to another. UAV could navigate automatically as the mobile data collector. It is free from the mobility limitation of ground transportation and can be used in particular monitored regions that might be unapproachable to humans.

1. *Quicker Data Collection* — Compared to ground data collection, aerial data collection uses a faster, controllable aerial vehicle. It could increase the speed of searching and visiting the nodes on structures and bridges. Using UAV, the data collection life cycle of the large wireless sensor network (e.g., encompassing large bridges and highways), spanning over many miles, can be greatly reduced.
2. *Performance* — The aerial data collection in UASHM often has fewer obstacles and larger coverage of wireless signals that lowers communication latency and increases the bandwidth.
3. *Heterogeneity* — Most amiable UAV/drones in the market allows for attaching external sensors and relaying the data back to a ground station using telemetry communication links. Moreover, a drone can (a) lift a certain payload, and (b) have (or easily mount) an expandable interface for attaching custom sensors to overcoming the limitation of single-purpose platforms, which are costly to cover for other tasks.

To date, there is no comprehensive study on the application of UAV assisted SHM for civil infrastructure. In this paper, we discuss several UAV civil applications and identify their main challenges. We also converse the research trends for UAV uses and future insights.

### *1.1. Contribution of the paper*

The main contributions of this paper are:

- Present research work distribution of SHM over a decade and discuss the shift in trends over the years.
- Present the payload product line to facilitate SHM tasks- classified based on the capacity, payload types, and identifies custom payload for specific use cases mentioned in literature.
- Detail the different applications of UAVs in civil structures as per the literature in the last decade; to categorize them into crack detection, delamination detection, displacement detection, and corrosion detection.

## 2. Methodology

The study underwent a systematic approach to identify literature discussing how Structural Health Monitoring (SHM) can be benefitted from the implementation of Unmanned Aerial Vehicles (UAVs). The literature studied was limited to the ones from 2012 to 2019 since most of the advancement in this field is recent. The search was performed using Google Scholar because it is a consolidated platform for seeking major contributions. A total number of 49 articles were selected among 190 extracted from the search. The selection process consisted of three steps. The first was to perform a search in Google scholar using a search string composed of *"UAV" and "SHM" or 'Drones' or 'Structural Health Monitoring' or "Unmanned Aerial Vehicles"*. The second step was to browse through abstracts and pick the top 10 relevant articles in a specific year. The third step was to read the entire article and exclude it from the study if it is not related to UAV assisted SHM.

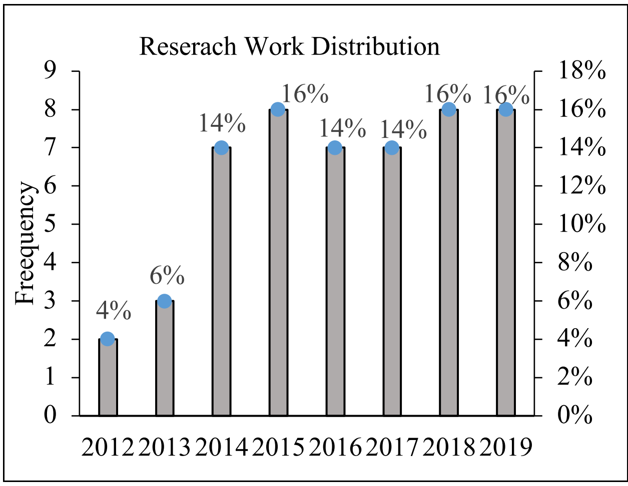


Figure 1: Distribution of UAV assisted SHM works through the years

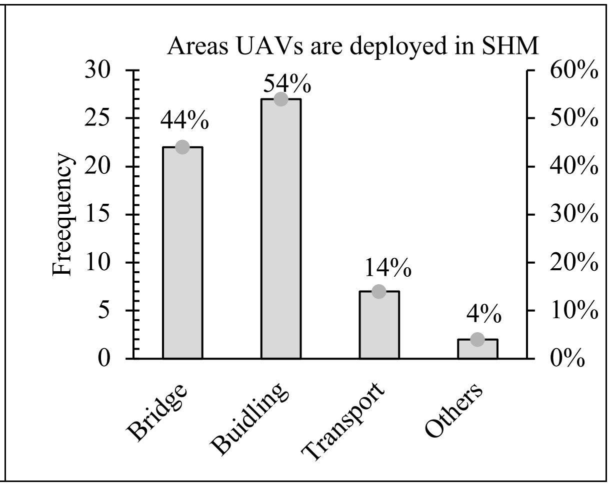


Figure 2: UAV deployment areas

## 3. Literature Review Findings

### RQ1. What is the distribution of research over the last decade for UAV assisted SHM?

Figure 1 shows the relatively non-uniform distribution of relevant literature papers during the past 8 years (2012-2019). From the year 2012, there has been a steady growth in the availability of relevant literature until 2015. A decline in the number of research articles is observed from the year 2016-2017. The graph also shows that there is considerable growth in related research from 2018. The year 2019 does not show a rise in the number of research papers compared to 2018. This is due to the fact that the survey is conducted in the middle of 2019. More relevant literature would fill up space in the graph as the year proceeds.

### RQ2. What are the different categories of civil structures for which UAVs have been used to monitor the structural health?

The aim of this research question is to identify the categories of civil structures for which UAVs have been employed for health monitoring. Figure 2 shows the main civil structure categories observed in the literature, for which either UAVs are used for SHM or a technique/methodology is proposed to support UAV assisted SHM. Thus civil structures are categorized into four major categories: bridges, buildings, transportation, and others. We detail each of the categories to better understand the adoption mechanism of UAV assisted SHM for each of them. In addition, we provide important insight into the improvements that the UAV industry should consider to facilitate SHM.

**Bridges-** They have an estimated lifespan of 50 years. According to the American Society of Civil Engineers (ASCE), there are about 614,387 bridges in the United States [21]. Of these, around one-fourth are classified as functionally obsolete and about 9.1% of them are classified as structurally deficient [21].

**Buildings -** They consist of factories, universities, aging historical buildings, etc. UAV assisted SHM was first exercised on buildings. According to Eschmann et al. [8], there is an increasing concern about their aging process. He continues to point out the difficulties with traditional man driven visual inspections as the choice of SHM methods [8].

**Transport-**They includes roads, pavements, and railway lines. One of the main benefits of UASHM is its ability to cover wide areas faster than conventional SHM. This ability makes it ideal for monitoring transportation infrastructure. Modern railway security systems used in infrastructure protection applications include a set of different sensing technologies integrated by appropriate management systems. Such systems are still highly dependent on human operators for supervision and intervention. One of the challenging goals of the research community in this field is the automatic detection of both natural and malicious threats. Flammini et al. [9] have illustrated the possibility of monitoring railway infrastructure using UAVs. The author pointed out that the recent innovations in the field of UAVs would enable UASHM in railway infrastructure to include wireless charging with RF energy, and wireless interaction between IoT (Internet of Things) devices associated with railway infrastructure [9].

**Others-** Apart from the mainstream civil structures, there are some other categories that stand out. Some examples are dams, tunnels, retaining walls, and wind turbines. They are unique in their design of build, and most often, traditional SHM methods are difficult to perform on them. For large-scale structures like retaining walls or dams, due to their immense size, a detailed all-embracing investigation is technically complex and time-consuming. Specially trained inspection engineers are needed to perform the assessment of structural stability. This complexity leads to very high costs, which often result in longer inspection periods causing deficits in detailed inspections and lack of safety.

**RQ3. What are the different payloads that are useful for SHM?**

The payload can be explained as the goods that can be carried by the UAV during flight. The goods in context to SHM could be data capturing devices, navigators, sensors, or any specific type of equipment the user wants the UAV to carry to facilitate the SHM. A higher payload capacity implies that they can carry more devices/attachments, thus indicating better applicability. Nowadays, the lack of lightweight high definition cameras and sensors pose a significant challenge for UAV assisted SHM, as has been highlighted in new research, but being that the requirement has been made known relatively recently, it will take time for lightweight payload devices to be developed. Major payload types are discussed below.

**3.3.1 Data acquisition devices**

There are a wide variety of devices and sensors that can be attached to UAVs to give an extra dimension to the data being collected. Some of the important ones are listed below.

*RGB Image/Video capturing device-* Undoubtedly one of the most important data collection devices used with UAVs, Image capturing devices are used to obtain digital images using vision sensors. They are lightweight and can easily be attached due to their compactness. One of the major use cases is surface damage detection. One advanced version of these is RGB-D sensors where in addition to RGB feature data, the sensor records per-pixel depths which can be useful for various purposes such as the 3D reconstruction of infrastructure.

*LiDAR (Light Detection and Ranging)* - LiDAR sensors use laser pulses in quick intervals to calculate the distance between the sensor and objects and map them into a 2D/3D image. LiDAR sensors are particularly useful in low light conditions where high accuracy 2D/3D models are required. For example, A. Khaloo et al. [19] showed how well LiDAR can be used with point-cloud techniques to extract features from infrastructure surfaces. LiDAR sensors are being adopted for UAV assisted SHM more commonly, and we are expected to observe a rising trend in the number of articles studying them in the future.

*NIR (Near Infrared )-*NIR sensors are expensive and rarely used. They combine RGB images with infrared and can be used to differentiate between various types of infrastructure surfaces.

***3.3.2*** **Navigation and control devices**

UAVs are steadily becoming more capable and easier to fly, in view of the advancement being made in navigation assistance sensors. These sensors provide much more control and stability over the flight and enable autonomous capabilities. Some important navigation systems that are used in UAVs are listed below:

***GPS (Global positioning system) -***GPS devices calculate their geographical position using a radio receiver to detect signals from satellites orbiting the earth. Combined with other sensors, GPS enables UAVs to detect their position accurately and even use geo-tagging to tag objects and locations when called upon. They have consequently become an indispensable part of UAVs.

***INS (Inertial Navigation System)-***INS uses a wide array of sensors like motion sensors and rotation sensors for dead reckoning the position, velocity, and orientation of the UAVs continuously [15]. The ability to correlate sensor readings is the main contributor to their success. Combined with GPS data, INS can be used to track UAV motion so that autonomous flight between geographical checkpoints is made possible during SHM.

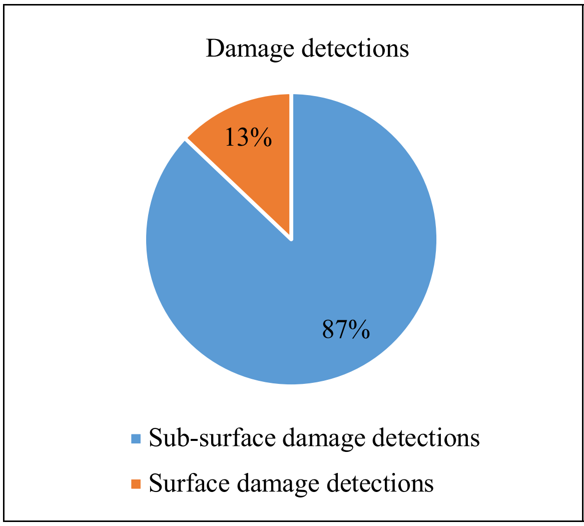


Figure 3: Primary classification of damage detections in the Research works

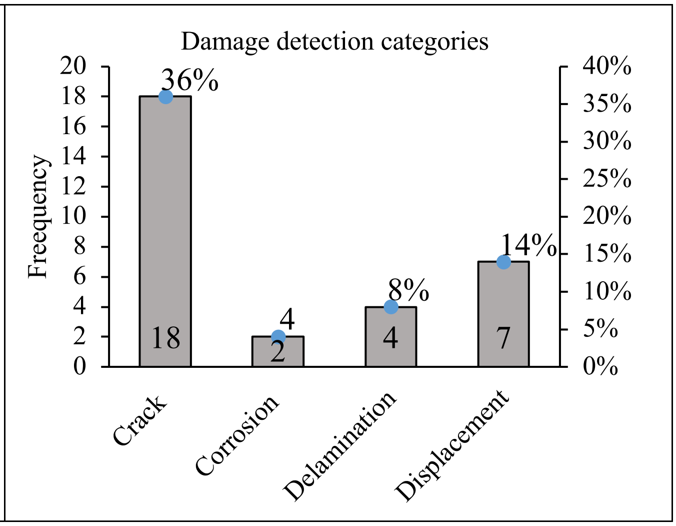


Figure 4: Data analysis techniques for various Damage detection categories

***Obstacle avoidance systems***- They are used to detect obstacles in the way of flight to avoid the collision. These devices use sensor data with techniques such as SLAM (Simultaneous Localization and Mapping) algorithms to intelligently steer the UAV away from obstacles.

***Geomagnetic sensors-*** These sensors are used to calculate the reference and heading of the UAVs in relation to the earth. It is made possible by reading the earth's magnetic field lines and analyzing its intensity against standard measurements.

### 3.3.3 Communication devices

These devices are used to communicate and transfer data between the UAV and its control/data receiving device. UAVs commonly use radio waves as a medium of communication. A specific radio frequency bandwidth is set as default between the UAV and the controller to enable communication between them. As a safety measure, RFIDs (Radio Frequency Identification) are provided to all devices, and the RFIDs of the UAV and controller must match for communication to be established.

### 3.3.4 Custom payloads for specific use cases

These are devices or materials that are mounted on UAVs for user-specific tasks. For example, Myeong et al. [12] demonstrated the use of wall-climbing UAVs that can fly and stick on walls to perform inspections. Here, the wall-sticking equipment can be considered as a special payload that is mounted for this user-specific case [12]. Similarly, various types of payloads have been observed that are significant for that specific user.

## RQ4. What are the different applications of UAVs to support civil structures that have been explored by researchers in the last decade?

With the recent advancement in the area of UAVs and the associated sensor devices, their applications in the field of structural health monitoring are limitless. With their greater freedom of movement, UAVs can get visuals of unattainable areas of civil structures that were previously considered near impossible through conventional methods. Their inspection methods are primarily visual, and they enlist the help of image capturing devices and sensors to detect damages and defects on infrastructure surfaces.

In the field of civil SHM, damage detection techniques can be categorized into 2 types as shown in **Error! Reference source not found.**, namely, surface damage detection and subsurface damage detection. As the name suggests, the former is visible on the surface of the civil infrastructure. They are relatively easier to inspect and identify with the help of conventional UAV data acquisition sensors like RGB cameras. The types of surface damage detection techniques that are discussed in UASHM are crack detection, corrosion detection, and displacement detections.

Sub-surface damages originate below the surface of the infrastructure and in most cases show no visual signs of developments at the surface. These are harder to detect with conventional visual data acquisition devices and as such, researchers generally use additional payloads such as Infrared sensors to detect them. The type of sub-surface damage detection this research study discusses is Delamination detection. To give an overview, Figure 3 shows that the majority (87%) of research studies concentrate on surface damage and the remaining 13% focus on sub-surface detection.

The studies are further classified into specific categories as represented in Figure 4 to understand the trends in UASHM research. These include crack detection, delamination detection, displacement detection, corrosion detection, and supporting work for the above-mentioned techniques.

***Crack detection*** - For detecting cracks in materials like concrete and metal. A majority of literature papers have addressed crack detection as the primary concern in infrastructure safety inspections, and rightfully so. They are the main cause of damage and fatalities in most cases.

Back in the year 2012, Eschmann et al. [8] investigated conventional means of inspecting large scale infrastructure and observed that the main goal was to analyze cracking conditions. Eschmann et al. [8] continued to point out the laborious nature of these procedures and underlined the importance of much-needed UAV assisted inspection methods. Although on-field experiments were promising, the struggles of mounting heavy payloads used for crack detection on UAVs were evident. Collected geo-referenced high-definition RGB images were stitched together to form a large 1.27 Gigapixel image, mostly done manually since it was too complex for the then-existing pattern recognition algorithms [8]. Detection of cracks was performed by applying Gaussian blur and greyscale intensity to the images and performing edge detection algorithms. The major drawback was that the method was successful only with white or grey walls [8].

Gopalakrishnan et al. [10] conducted a case study on UAV assisted SHM focused on crack detection using pre-trained VGG-16 DCNN (Deep Convolutional Neural Network), a highly recommended model by researchers for transfer learning as it is trained on a large data set with highly optimized hyper-parameters. The authors compared the results with other techniques like SVM (Support Vector Machines), RF (Random Forest), and ERT (Extremely Randomized trees) with classical NN (Neural Networks) and LR (Logistic Regression) techniques which are trained on the pre-trained VGG-16 DCNN [10]. Performance results justified the claim that both NN (Neural Networks) and LR (Logistic Regression) achieved 89% accuracy in testing [10]. The authors also pointed out the opportunities that exist for building the DL (Deep Learning) model capable of identifying multiple types of defects and the need to integrate UAV based SHM with big data systems such as MapReduce and Hadoop to manage complex computing requirements of crack detection algorithms [10].

One of the challenges of implementing DL based crack detection techniques in UAVs is their latency caused by the complexity in calculations and the need for brute force computational needs. To address this issue, Cha et al. [4] introduced a time-efficient method to identify multiple-damage types with Deep Learning algorithms. As opposed to the conventional approaches, authors used a region-based model, called Faster R-CNN (a type of Convolution Neural Network with 'R' stands for Region) to identify multiple damage types. Faster R-CNN is a region-based technique where a convolutional feature map is generated by passing images through CNN, following which region proposals are performed with the help of an additional region proposal network and then RoI (Region of Interest) pooling fixes them into standard sizes (mostly down-sampling) [16]. Softmax activation methods work well for multi-classifications on CNN [16]. Faster R-CNN is quicker because it prevents featureless regions from passing through the entirety of the time-consuming analysis process and uses a quicker region proposal network instead of slow special region proposal methods. Having low latency algorithms like this is promising since it can be implemented in a UAVs' onboard computer so that it could unveil real-time detection methods [4].

***Delamination detection***- this technique focuses on the damaged layers formed on the surface as a result of the material losing its coating adhesion. It is commonly seen on concrete surfaces. Multiple attempts notwithstanding, identifying delamination defects had proven to be painstaking. According to our observation, the first literature out of the selected ones, that addresses this issue, came out in the year 2016. Ellenberg et al. [7] tried to tackle this by implementing IR (infrared) sensors in the UAVs. FLIR a325sc delamination detection algorithm was used to identify surface delamination [7]. The experiment was successfully conducted on a bridge deck. Omar and Nehdi [13] adopted the same approach as Ellenberg et al [7]. The IRT (infrared thermography) technique for subsurface delamination worked on a simple principle. When the surface is under sunlight, it absorbs radiation and heats up the areas where delamination has occurred. Those areas tend to have lesser heat transfer due to their detachment from the main structure, resulting in increased temperatures relative to the surrounding surface. These areas of higher temperature can be identified as “hot spots” by IRT sensors mounted on the UAVs during inspection [13].

Dorafshan and Maguire [6] discovered that delamination detection efficiency might vary according to data collection methods. The authors suggested that standard procedures such as ASTM D4788-03, an IRT (infrared thermography) based standard test, could address this concern. As sensors are becoming lightweight and compact, future development of higher resolution IRT sensors with better sensitivity could result in improved UAV assisted delamination detection.

***Displacement detection –*** Defects due to displacement are formed when a portion of the entire structure or the structure as a whole is moved away in relation to its original position of reference. This could compromise the structural integrity of the structure so much so that the need for identifying these defects is one of the major priorities in health inspection.

One straight forward example of displacement defect would be the retaining walls we see beside roads. The first detailed study on displacement detection among the selected research papers took place in the year 2014 where Hallermann and Morgenthal [5] examined a large retaining wall for potential displacement defects. These walls retained landmass, which was elevated with respect to the road and prevented landslides by providing extra support. Eventually, due to the extreme amount of pressure caused by the landmass, they would develop a tendency to push away along the direction of pressure. These kinds of displacements could be visually identified easily from a distance. Hallermann and Morgenthal [5] tested the potential of UAVs for displacement detection using photogrammetric methods and computer vision algorithms. The test case, a 700m long retaining wall with a height of 20m and an inclination of 70 degrees, which was examined using UAVs and generated airborne images for analysis. They validated the accuracy of the method by removing some of the bricks intentionally and replacing a few with thinner plates to simulate the movement of the portions [5]. The images were collected from the same pre-planned flight path of UAV and both cases were compared for detecting displacement [5].

***Corrosion detection*** – Since metals are widely used as parts of building infrastructure, the possibility of corrosion is omnipresent. Corrosion is a natural phenomenon commonly occurring in metals where it undergoes an electrochemical process to liberate positive charge and become a stable compound. When these corroded components begin to degrade, they become a weak link for the entire structure. Yeum and Dyke [14] brought up the need for corrosion detection in UAV assisted SHM in the year 2015. Even then, authors could not introduce any detection technique that solely focused on corrosion detection rather than depending on traditional vision-based inspection methods [14]. Following the same path, Henrickson et al. [11] considered corrosion detection for their UAV based infrastructure assessments but were unsuccessful in the development of any effective method.

Ellenberg et al. [17] introduced one of the tested and validated techniques for corrosion detection. The experiment was conducted in two ways. The first one was performed manually with the help of MatLab and Paint applications. The second approach was to apply K-means algorithms to determine the size of the corroded areas. The experiment was performed with minimal errors where the manual method (10% error) achieved a slight edge over the K-means algorithms method (15% error) [17]. Unfortunately, we were unable to find any method in the article which could detect corroded areas in the first place.

Cha et al. [4] ultimately developed a relatively robust model in the year 2018, which had the capability of detecting two types of corrosion: steel corrosion, and bolt corrosion. The corrosion in steel occurs when iron in the compound starts to oxidize and produce rust, rendering it weak. In the case of the bolt, localized corrosion happens between two joints of the metal surface, and it is usually more aggressive. As we mentioned earlier, Cha et al. [4] used the Faster R-CNN model to detect multiple damage types. Since it was a region-based model, this technique best-suited corrosion detection [4]. The many-steps process ended with the Softmax method for the final classification. In addition, Cha et al. [4] categorized steel corrosion into two: medium steel corrosion and high steel corrosion. This move was intended to improve the accuracy of the model and it worked out to be excellent for a high-speed algorithm like Faster R-CNN. The average precision of the models was documented to be around 82% for High steel corrosion and 84% for Medium steel corrosion [4]. Bolt corrosion precision was recorded to be around 90%, which was promising considering the 38 test cases that authors tried on [4].

## References

[1] Bordel, B., Alcarria, R., Martín, D. et al. J Ambient Intell Human Comput (2017) 8: 485.

[2] Ellenberg, A., Kontsos, A., Bartoli, I., & Pradhan, A. (2014a). Masonry Crack Detection Application of an Unmanned Aerial Vehicle. Computing in Civil and Building Engineering (2014).
[3] Carletti, V., Greco, A., Saggese, A. et al. ( 2019) J Ambient Intell Human Computing . https://doi.org/10.1007/s12652-019-01212-6
[4] Cha, Y. J., Choi, W., Suh, G., Mahmoudkhani, S., & Büyüköztürk, O. (2018). Autonomous Structural Visual Inspection Using Region-Based Deep Learning for Detecting Multiple Damage Types. Computer-Aided Civil and Infrastructure Engineering, 33(9), 731–747. https://doi.org/10.1111/mice.12334
[5] Hallermann, N., & Morgenthal, G. (2014). Visual inspection strategies for large bridges using Unmanned Aerial Vehicles (UAV). Bridge Maintenance, Safety, Management and Life Extension, (December), 661–667. https://doi.org/10.1201/b17063-96
[6] Dorafshan, S., & Maguire, M. (2018). Bridge inspection: human performance, unmanned aerial systems and automation. Journal of Civil Structural Health Monitoring (Vol. 8). Springer Berlin Heidelberg.
[7] Ellenberg, A., Kontsos, A., Moon, F., & Bartoli, I. (2016). Bridge deck delamination identification from unmanned aerial vehicle infrared imagery. Automation in Construction, 72, 155–165.
[8] Eschmann, C., Kuo, C.-M. C.-H. M. H., Kuo, C.-M. C.-H. M. H., & Boller, C. (2012). Unmanned Aircraft Systems for Remote Building Inspection and Monitoring. 6th European Workshop on Structural Health Monitoring 2012, EWSHM 2012, July 3, 2012 - July 6, 2012, 2, 1179–1186.
[9] Flammini, F., Pragliola, C., & Smarra, G. (2017). Railway infrastructure monitoring by drones. 2016 International Conference on Electrical Systems for Aircraft, Railway, Ship Propulsion and Road Vehicles and International Transportation Electrification Conference, ESARS-ITEC 2016, (November). https://doi.org/10.1109/ESARS-ITEC.2016.7841398
[10] Gopalakrishnan, K., Gholami, H., & Agrawal, A. (2018). Crack Damage Detection in Unmanned Aerial Vehicle Images of Civil Infrastructure Using Pre-Trained Deep Learning Model. International Journal for Traffic and Transport Engineering, 8(1), 1–14. https://doi.org/10.7708/ijtte.2018.8(1).01
[11] Henrickson, J. V., Rogers, C., Lu, H. H., Valasek, J., & Shi, Y. (2016). Infrastructure assessment with small unmanned aircraft systems. 2016 International Conference on Unmanned Aircraft Systems, ICUAS 2016, 933–942. https://doi.org/10.1109/ICUAS.2016.7502652
[12] Myeong, W. C., Jung, K. Y., Jung, S. W., Jung, Y. H., & Myung, H. (2015). Development of a drone-type wall-sticking and climbing robot. 2015 12th International Conference on Ubiquitous Robots and Ambient Intelligence, URAI 2015, (Urai), 386–389. https://doi.org/10.1109/URAI.2015.7358881
[13] Omar, T., & Nehdi, M. L. (2017). Remote sensing of concrete bridge decks using unmanned aerial vehicle infrared thermography. Automation in Construction, 83(June), 360–371.
[14] Yeum, C. M., & Dyke, S. J. (2015). Vision-Based Automated Crack Detection for Bridge Inspection. Computer-Aided Civil and Infrastructure Engineering, 30(10), 759–770. https://doi.org/10.1111/mice.12141
[15] Inertial navigation system. (2019, June 22). Retrieved from https://en.wikipedia.org/wiki/Inertial_navigation_system
[16] Gandhi, R. (2018, July 09). R-CNN, Fast R-CNN, Faster R-CNN, YOLO –Object Detection Algorithms. https://towardsdatascience.com/r-cnn-fast-r-cnn-faster-r-cnn-yolo-object-detection-algorithms-36d53571365e
[17] Ellenberg, A., Kontsos, A., Moon, F., and Bartoli, I. ( 2016) Bridge related damage quantification using unmanned aerial vehicle imagery. Struct. Control Health Monit., 23: 1168– 1179. doi: 10.1002/stc.1831.
[18] Ramirez-Atencia, C. & Camacho, D. J Ambient Intell Human Comput (2019) 10: 2467.
[19] Khaloo, A., Lattanzi, D., Cunningham, K., Dell'Andrea, R., & Riley, M. (2017). Unmanned aerial vehicle inspection of the Placer River Trail Bridge through image-based 3D modelling. Structure and Infrastructure Engineering,14(1), 124-136. doi:10.1080/15732479.2017.1330891
[20] Morgenthal, G., & Hallermann, N. (2014). Quality Assessment of Unmanned Aerial Vehicle (UAV) Based Visual Inspection of Structures. Advances in Structural Engineering, 17(3), 289–302. doi: 10.1260/1369-4332.17.3.289
[21] Ironcore. (2016). Report card for Bridges in USA. Retrieved from https://www.infrastructurereportcard.org/cat-item/bridges/.