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Bridge Inspection and condition assessment using Unmanned Aerial Vehicles (UAVs): Major challenges and solutions from a practical perspective

Hyung-Jo Jung*, Jin-Hwan Lee[a], Sungsik Yoon[b] and In-Ho Kim[c]

Department of Civil and Environmental Engineering, Korean Advanced Institute for Science and Technology, 291 Daehak-ro, Yuseong-gu, Daejeon 34141, Republic of Korea

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Abstract. Bridge collapses may deliver a huge impact on our society in a very negative way. Out of many reasons why bridges collapse, poor maintenance is becoming a main contributing factor to many recent collapses. Furthermore, the aging of bridges is able to make the situation much worse. In order to prevent this unwanted event, it is indispensable to conduct continuous bridge monitoring and timely maintenance. Visual inspection is the most widely used method, but it is heavily dependent on the experience of the inspectors. It is also time-consuming, labor-intensive, costly, disruptive, and even unsafe for the inspectors. In order to address its limitations, in recent years increasing interests have been paid to the use of unmanned aerial vehicles (UAVs), which is expected to make the inspection process safer, faster and more cost-effective. In addition, it can cover the area where it is too hard to reach by inspectors. However, this strategy is still in a primitive stage because there are many things to be addressed for real implementation. In this paper, a typical procedure of bridge inspection using UAVs consisting of three phases (i.e., pre-inspection, inspection, and post-inspection phases) and the detailed tasks by phase are described. Also, three major challenges, which are related to a UAV's flight, image data acquisition, and damage identification, respectively, are identified from a practical perspective (e.g., localization of a UAV under the bridge, high-quality image capture, etc.) and their possible solutions are discussed by examining recently developed or currently developing techniques such as the graph-based localization algorithm, and the image quality assessment and enhancement strategy. In particular, deep learning based algorithms such as R-CNN and Mask R-CNN for classifying, localizing and quantifying several damage types (e.g., cracks, corrosion, spalling, efflorescence, etc.) in an automatic manner are discussed. This strategy is based on a huge amount of image data obtained from unmanned inspection equipment consisting of the UAV and imaging devices (vision and IR cameras).

Keywords: bridge inspection; unmanned aerial vehicle (UAV); imaging device; condition assessment; deep learning algorithm

1. Introduction

Bridge collapse suddenly happens unexpectedly, resulting in a big impact on our society in a very negative way. There are many reasons why a bridge collapses, such as a combination of problems, design faults and manufacturing errors, and poor maintenance. A number of problems or combinations of factors are the main reasons why bridges fail. If they happen individually, the bridge will not fall. But when they happen at once, they have catastrophic consequences. Design flaws and manufacturing errors were other major reasons. However, they are becoming less common than in the past. Instead, poor maintenance is becoming a major contributor to the recent collapse. Also, the aging of bridges can make the situation worse. The fall of the Silver Bridge on the Ohio River in 1967 and the collapse of the Sungsoo Bridge in the Han River in 1994 are well known as two of the bridge collapses in the US and Korea. Even if the years of the occurrence are different, these two tragic collapses brought about national interests and concerns about safety checks and bridge maintenance in both countries.

In the case of the United States, it was reported that about 10% of total bridges were structurally deficient in 2016 (ASCE 2017). The more problematic thing was its average age of about 43 years (ASCE 2017). As noted before, the aging of bridges will make the situation worse. As for Japan, half of the total bridges will be more than 50 years old in 2030 (Fujino and Takada 2008). Korea and China are a little bit better situation because these countries were developed relatively late. However, it is known that the aging of infrastructure is inevitable. Thus, an appropriate measure should be prepared in advance. That is, bridge maintenance has become an important task for the government as well as bridge engineers.

In order to secure public safety and structural reliability, it is indispensable to conduct timely maintenance such as bridge inspection and condition assessment. In other words, bridge inspection to check out the condition of a bridge, which have suffered from various damages such as cracks, corrosion, efflorescence, spalling and exposed rebar during its lifespan, is needed. Visual inspection is the oldest and

*Corresponding author, Professor
E-mail: hjung@kaist.ac.kr
[a] Ph.D. student
[b] Ph.D. student
[c] Post-doctoral researcher

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most frequent type of bridge inspection (Dorafshan and Maguire 2018), but it heavily depends upon the experience of the inspectors, and it is time-consuming, labor-intensive, costly, disruptive, and even unsafe for the inspectors. This conventional method may also require special equipment such as under-bridge units and skilled personnel. Thus, a new approach to overcome the limitations of the current approach should be required.

In recent years, an increasing interest has been paid to the use of an unmanned aerial vehicle (UAV) in many areas. Of course, bridge inspection area is no exception. Due to many attractive features of a UAV equipped with imaging devices such as visual cameras, it is expected to address many limitations of the conventional inspection approach. That is, the use of a UAV can make the inspection process safer, faster, and more cost-effective (Dorafshan and Maguire 2018). In addition, it can inspect members or spots that are difficult for the inspector to reach, for example, the upper part of a main tower in a long-span bridge. Because of these potential advantages, bridge inspection using UAVs has received fast growing interests in many countries including the United States, Europe, Australia, Japan, China, and Korea (Chen *et al.* 2019, Darby *et al.* 2019, Jung *et al.* 2019). Initially, the demonstration or trial projects were mainly conducted for validating its feasibility. For example, many state Departments of Transportation (DOTs) have conducted demonstration projects using UAVs to identify damage on several bridges in the United States (Moller 2008, Irizarry and Johnson 2014, Brooks *et al.* 2015, Lovelace and Zink 2015, Otero *et al*. 2015, Wells and Lovelace 2017). It seems that their main purpose is to make routine inspection more economical, faster, and safer by simply replacing naked eyes of inspectors with imaging devices mounted on UAVs.

Even though there is a lot of interest around the world, there are still a number of limitations and constraints to the practical application of this technology. Chan *et al*. (2015) summarized challenges for UAV implementation as follows: regulation of governing authorities, limitations for superstructure and substructure components, visual observation, fail-safe programming and obstacle avoidance, and localization of UAVs in the Global Positioning Systems (GPS) denied environment. Dorafshan and Maguire (2018) added a few more challenges such as automated or semi-automated tool development mainly for post-processing operations and weather conditions (e.g., variable lighting conditions underneath a bridge, high wind speeds, etc.).

In addition to addressing the limitations and constraints of bridge inspection using UAVs, many studies are also being actively conducted to maximize the potential of imaging devices mounted on the UAV and to utilize actual bridge condition assessments and ratings. In particular, Morgenthal *et al*. (2019) proposed a comprehensive framework for automated UAV-based bridge inspection and condition assessment. Their framework includes 3-dimensional (3D) flight path planning, high-precision 3D bridge element reconstruction, automated image analysis for feature detection, and mechanical interpretation of acquired data using point cloud analysis methods for calibration of numerical models. It was demonstrated with a realistic case study that their methodology could be used for an intelligent and potentially autonomous safety assessment of bridge structures. However, they did not explicitly address some important technical challenges that could cause problems when applying UAVs to real bridges, such as GPS shaded area flight and identification of various damages. It is necessary to draw out the challenges from the practical perspective and examine the technologies that can solve them. In addition, in order to effectively utilize this technology for detailed bridge safety diagnosis as well as routine inspection, it is necessary to obtain a technique that can distinguish a crack width of about 0.3 mm because it is the allowable maximum crack width of concrete structures (Wu 2015). However, previous studies have rarely considered issues related to this accuracy.

This paper deals with a UAV-based bridge inspection and condition assessment strategy by focusing on major challenges and their possible solutions. To do so, the three major technical challenges in bridge inspection using UAVs are first identified from a practical point of view after describing a typical procedure of bridge inspection using UAVs. And, corresponding potential solutions for addressing the major challenges, which have been recently developed or are being developed, are presented and discussed.

2. Typical UAV-based bridge inspection procedure and major challenges from a practical perspective

In this chapter, the typical procedure for inspecting a bridge structure using UAVs are first explained. Although specific details may vary slightly depending on the purpose of the inspection, the target bridge, and the surrounding environment, here are some common procedures that can be performed in common UAV-based bridge inspection. Duque (2017) presented a UAV-based bridge inspection protocol consisting of five stages (i.e., bridge information review, site risk assessment, drone pre-flight setup, drone-enabled bridge inspection, and damage identification). He also developed a UAV-image-based damage quantification protocol to efficiently identify and quantify damage on the bridge. On the other hand, Morgenthal *et al*. (2019) presented the 8-step inspection processes: preparation, flight path generation, UAV-based data acquisition, photogrammetric 3D reconstruction, anomaly detection, 3D modeling and visualization, mechanical interpretation, and structural condition assessment. In this study, the entire procedure can be simply divided into three stages: Pre-Inspection, Inspection, and Post-Inspection. Fig. 1 shows the overall inspection procedure presented in this study. Each stage has its own tasks as seen from the figure.

2.1 UAV-based bridge inspection procedure

2.1.1 The Pre-inspection phase

The pre-inspection stage is a necessary step to successfully perform bridge inspection using UAVs. It is the preparation stage for the main inspection, analyzing the preliminary information about the bridge to be inspected

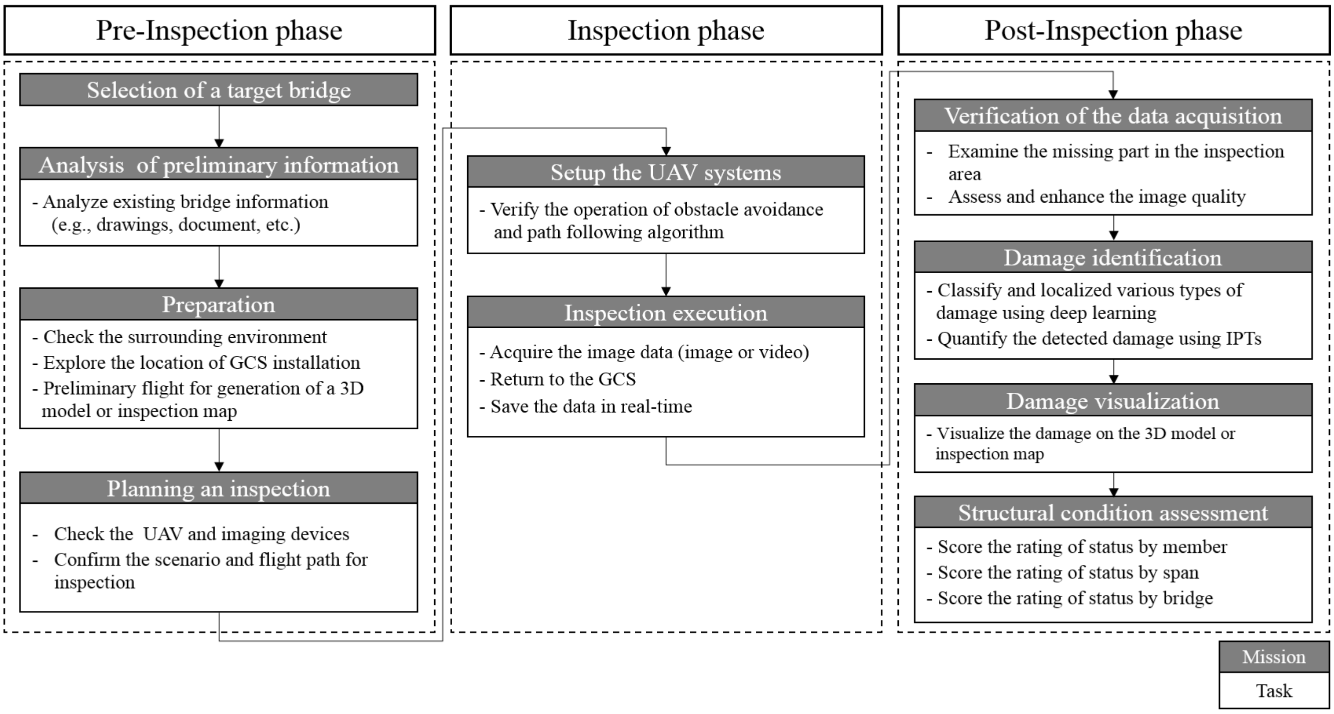


Fig. 1 Typical procedure of bridge inspection using UAV

and specifying the inspection plan through the preliminary exploration. Detailed steps and tasks in this stage can be found in Fig. 1. As seen from the figure, the bridge to be inspected should be first selected and the basic information about the bridge should be collected, organized, and analyzed. Also, the surrounding environment of the target bridge and the proper location of the ground control station (GCS) for UAV navigation should be carefully examined. Checking the status of the UAV and the imaging devices such as vision cameras to be mounted is also one of the primary tasks to be performed at this stage.

If the key information about the bridge does not exist or if the information is not enough, it must be obtained through a preliminary flight during the pre-site visit before the main inspection stage. Through this activity, it is possible to generate a 3D model which can provide a virtual map for the UAV to navigate around the bridge and avoid obstacles. That is, the 3D model can be used for the flight path and inspection scenario planning. However, it is noteworthy that the detailed 3D model of a bridge for purposed of damage identification has not been constructed successfully yet (Dorafshan and Maquire 2018). The information acquired from the preliminary flight can be also used to generate the inspection map for damage history management.

2.1.2 The Inspection phase

In the main inspection stage of the conventional approach, the highly trained inspector performs visual inspection at close range, but in the case of UAV-based bridge inspection, the UAV approaches to the inspection area (i.e., the region of interest) and moves according to the preset path. At this stage, the success or failure of the mission may change depending on changes in the surrounding environment such as wind, sunlight, and shade. Especially, in case of inspecting the bottom of the bridge deck, countermeasures are needed because the GPS signal commonly used in the UAV flight cannot be used. Also, when inspecting with the UAV, make sure that UAV follows the path so that there are no missing areas. It is more effective to use a specially designed UAV with a proper performance for bridge inspection rather than using a general purpose UAV in order to perform them stable.

The final goal of the inspection phase is to secure image data having sufficient quality without missing parts of the inspection area by using UAVs equipped with the imaging device. This step has the procedure for the UAV to access the inspection area, perform the given mission, and return home. The procedure within the step is simple, but many considerations need to be taken in order for this process to be successful. In particular, there are many requirements related to the function or performance of a UAV, and a more detailed discussion on technical challenges in this stage will be given in the next section.

2.1.3 The Post-inspection phase

The overall procedure of the post-inspection phase is as follows: various types of damage in each member are first identified based on the image data obtained in the previous stage; then, the condition assessment is performed at the member level and span level, and finally, the condition assessment is performed on the entire bridge. To this end, the missing part in the inspection area and the quality of the acquired image data should be examined first, and if necessary, the process of enhancing the image quality can be performed. Next, various types of damage should be identified on a per-member basis and quantified by the type of damage with image processing techniques (IPTs), and the

Table 1 Challenges and major challenges identified from each phase

Phases	Challenges	Major Challenges
Pre-Inspection	- No document / drawings - Regulation of governing authorities - 3D model or inspection map generation - Limitations for superstructure and substructure components	
Inspection	- Localization of the UAV in the GPS denied environment - Collision avoidance - Weather condition (wind, sunlight) - Longer inspection time required - Camera location, payload capacity - Low illumination	1. Flight related challenges (GPS denied environment & limited UAV performance)
Post-Inspection	- Missing part in the inspection area - Quality of images acquired from UAVs - A huge amount of image data - Various damage types (crack, spalling, corrosion, efflorescence, etc.) - Damage classification/localization/quantification - Automation of damage identification - False alarm - Visualization of damage on the 3D model or inspection map	2. Data acquisition related challenges (Missing part in the inspection area & quality of image data) 3. Damage identification related challenges (Damage detection of various damage types from a huge amount of image data & false alarm)

detected damage can be integrated into the 3D model or the inspection map. Condition evaluation for each member is performed with this quantified data. These results are combined to evaluate the span level, and finally, the condition of the bridge is assessed. The subsequent rating process is followed by maintenance guidelines. Finally, these results can be compared with the previous data to review the progress of the damage and provide repair and retrofit measures, if necessary.

2.2 Challenges identified from each phase

At this section, detailed challenges during the UAV-based bridge inspection procedure are presented and discussed. Table 1 shows a summary of the challenges in each phase. After identifying challenges in each phase, more important and difficult technical ones from a practical point of view are taken into consideration, which are called ‘major challenges’ as listed at the last column in the table.

2.2.1 Challenges in the pre-inspection phase

In the pre-inspection phase, there are many challenges related to the bridge information review and analysis such as no document and drawings. In addition, regulation of governing authorities may hinder the use of UAVs. When bridges that contain road underpasses are considered to be inspected, UAVs are unfeasible for substructure and superstructure components (Chan *et al.* 2015). 3D model or inspection map generation for flight path planning or damage visualization is also another challenging task in the pre-inspection phase.

2.2.2 Challenges in the inspection phase

In the inspection phase, there are also many challenges associated with the mission, because the UAV has to perform near the inspection area of the bridge. There are the localization issue in the GPS denied environment, the weather condition such as strong wind and sunlight change, and others. Most of them may come from the surroundings of a target bridge. Another factor is related to the UAV’s performance. In other words, the UAV should fly longer because of the longer inspection time required, and it should have the capability of collision avoidance as well as sufficient payload capacity and versatility of camera location.

2.2.3 Challenges in the post-inspection phase

In the post-inspection phase, there are a number of challenges involved in detecting damage and assessing the condition. First, it is quite challenging to secure high-quality image data from the missing part-free inspection area. Next, various damage types (e.g., crack, spalling, corrosion, efflorescence, etc.) should be detected by using damage classification/localization methods. Also, the damage quantification issue will be followed. If this process is manually operated, it will be too time-consuming, thus this damage identification should be automated. The false alarm is one of the critical challenges in this phase as well.

2.2.4 Three major challenges from a practical perspective

As seen in the previous sections, there are many challenges in each phase. Some of them are not difficult to solve and some cannot be addressed by researchers (e.g., regulation of governing authorities). In this study, three major challenges are selected, which are considered as crucial issues to be addressed for applying UAVs to detailed bridge safety diagnosis as well as routine inspection from a practical point of view. They are listed in the last column of

Table 1.

The first major challenge is related to UAV flight. These include the challenges that impede the ability of a UAV to fly around the bridge without any difficulty and to inspect the bridge condition. This includes the issues related to localization of the UAV in the GPS denied environment and limited UAV performance for bridge inspection such as short flying time (or short inspection time using the UAV) and limitation on accessibility to a narrow space.

The second major challenge is related to the secure acquisition of the image data. Even if the UAV can freely fly for bridge inspection, it may not be possible to secure all the image data for all inspection areas due to various external environmental factors, and there may be problems with the missing part in the inspection area and the quality of the captured image data. These challenges need to be addressed thoroughly for the next step, the damage identification, to be successful.

The third major challenge is about quick and accurate damage identification and quantification from the vast amount of image data obtained from the UAV. To solve this problem, it is not possible to use conventional image processing techniques and manual processes. Faster and more automated techniques are needed, and methods to minimize false alarm should also be developed.

3. Solutions for addressing major challenges

In this chapter, technologies that have been recently developed or are being developed are presented and discussed to address the three main challenges selected in the previous chapter. First, the techniques for solving the UAV flight related challenges are described, and then the solutions to major challenges related to securing sufficient quality image data are dealt with. Third, the strategies for quickly and accurately processing a huge amount of image data have been discussed to detect and quantify multiple damage types, and the false alarm issue is also dealt with.

3.1 Flight related challenges

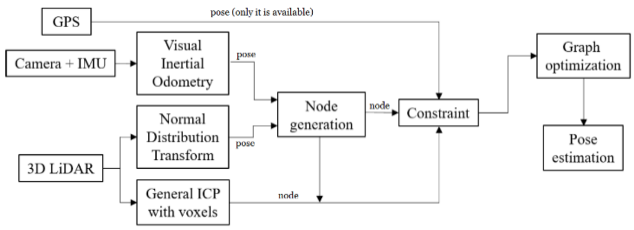
The first major challenge is the technical limitations associated with UAV flight. That is, in order to properly check the appearance of a bridge, the UAV should be able to freely fly around the bridge, and there are cases where such access is restricted for various reasons. The first and biggest hurdle is the GPS denied environment. If the UAV cannot fly under the bridge due to this challenge, the bridge inspection procedure cannot be successfully conducted. Another one is about the limited performance of a UAV used for inspection. The UAV must have the functions and performance that are essential for bridge inspection, but most commercial UAVs do not have some of them. In some cases, detailed inspection of the small specific area may be necessary, but this task cannot be performed with existing UAVs. Resolving these issues will certainly complete the first step of a bridge inspection strategy using UAVs.

3.1.1 GPS denied environment

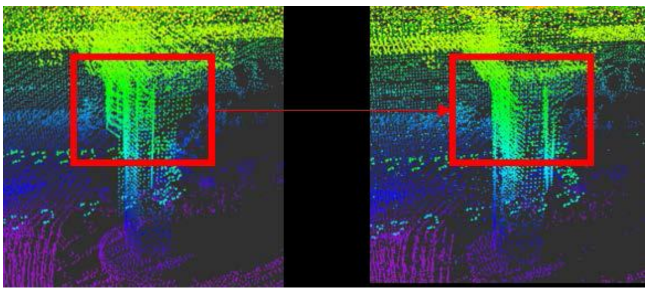
One of the most prominent technical challenges in the UAV-based bridge inspection is how to operate the UAV under the GPS denied environment like underneath the large bridge deck. In order to successfully complete the mission, a technique to localize a UAV without the GPS signal is needed. In addition, it is able to help to accurately identify the cracks or other damage types of the bridge.

A GPS denied environment under a bridge decreases the stability of the UAV platform. Thus, many flight planning methods using appearance image-based recognition (Han *et al.* 2015), simultaneous localization and mapping (SLAM) (Munguia *et al.* 2016), and Lidar odometry mapping in real-time (LOAM) (Sabatini *et al.* 2014) have been proposed to reduce the GPS error. Other researchers proposed and investigated a protocol for bridge inspection to address the challenges (Kim *et al.* 2017, Eschmann *et al.* 2013, Pereira *et al.* 2015). In addition, previous works used a method of generating three-dimensional information of a bridge by using images taken from the UAV and commercial tools (Hallerman and Morgenthal 2014, Chen *et al.* 2018) or mapping a bridge by using a LiDAR or a Leica geometry equipment at a lower part of a bridge and then using those data in the UAV (Khaloo *et al.* 2018, Delgado *et al.* 2017). However, most of them are based on the prebuilt map and cannot acquire real-time pose of the UAV under the bridge.

One of the representative solutions proposed by Song *et al.* (2018) is an image-based position estimation algorithm using a camera in addition to a conventional LiDAR (Light Detection And Ranging) sensor and a GPS sensor and IMU (Inertial Measurement Unit) embedded in the UAV.



(a) Overall flow diagram of the graph-based SLAM algorithm



(b) Matching result using the graph-based SLAM algorithm

Fig. 2 Graph-based SLAM algorithm for addressing the GPS denied environment issue (Song *et al.* 2018)

They developed a novel strategy for SLAM method under large bridges. The overall flow diagram of the proposed method is shown in Fig. 2(a). Basically, it is based on graph-structured SLAM. Sensors that are attached to UAVs are cameras, IMU, GPS, and 3D LiDAR, which are received as data and utilized in SLAM's structure. Because GPS signals are not detected at the bottom of the bridge, GPS data were used as information of nodes only when GPS signals were received. As shown in the figure, the Visual Initial Odometry (VIO) results are calculated by using camera images and IMU data. For robustness, a combination of the VIO estimate and the 3D LiDAR data is input to a graph structure of SLAM. In the algorithm, the VIO estimate is used for local pose estimation to approve the better accuracy of 3D LiDAR matching, and the 3D LiDAR matching is used for not only local pose optimization with Normal Distribution Transform but also global pose-graph optimization with General ICP with voxels. Fig. 2(b) shows the enhanced performance of the developed graph-based SLAM algorithm.

3.1.2 Limited UAV performance for bridge inspection

The next challenge is about whether the UAV is suitable for bridge inspection or not. In many previous studies, commercially available UAVs such as DJI Phantom 4 and DJI Inspire 2 were used for inspecting bridges. However, they are general purpose UAVs, so there some limitations for performing a specific mission. Typical examples are the lack of inspection time which is highly dependent upon payload, and the ability to overcome wind speed and limit camera installation.

To address these challenges, a customized UAV is needed. In other words, the UAV's performance is being enhanced to more effectively use it for bridge inspection. Through previous challenge identification process, one can list up some features bridge inspection UAVs should have. First, in order to successfully complete the inspection using UAVs for at least one span at a time, its flying time should be extended considerably. For example, pure inspection time should be guaranteed for at least 20 minutes, and it means that its flying time should be extended at least 30 minutes with a payload of more than 4.2 kg. Also, it should be robust to wind condition change. It is able to fly without any difficulty under the maximum instantaneous wind speed of 10 m/s and should have the path following capability because strong winds or gusts are likely to occur around the bridge. In addition, the installation position of an imaging device such as a vision camera should be adjustable according to the purposed of inspection. If the imaging device is installed at the front side, it can inspect the upward direction (e.g., the bottom surface of the deck) as well as the forward direction (e.g., the surface of the pier). To this end, a gimbal with 180-degree vertical rotation can be designed. These functions of UAVs required for bridge inspection are summarized in Table 2. Fig. 3 shows the schematic of a customized UAV having all the functions or capabilities mentioned above.

Table 2 Functions of UAVs required for bridge inspection

Function required	Description
Flying time (inspection time)	At least 30 min. (20 min.) subject to payload of 4.2 kg
Minimum Payload	About 4.2 kg (various sensors such as a 3D LiDAR and a DSLR camera, and a mini PC)
Wind resistance capacity	Stable flight under the maximum instantaneous wind speed of 10 m/s; path-following capability
Location of imaging devices	The front side for inspecting the upward direction as well as the forward direction

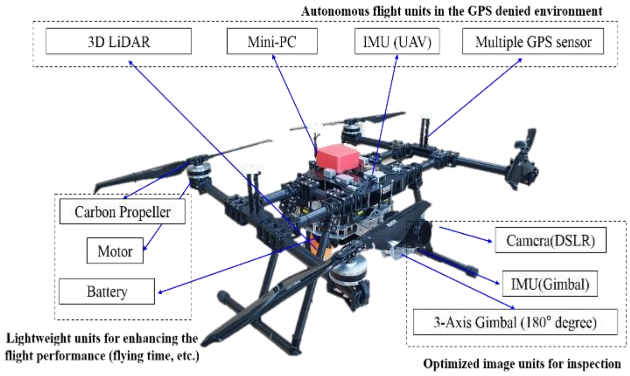


Fig. 3 Performance-enhanced UAV platform

3.1.3 Limitation on the accessibility to a narrow space

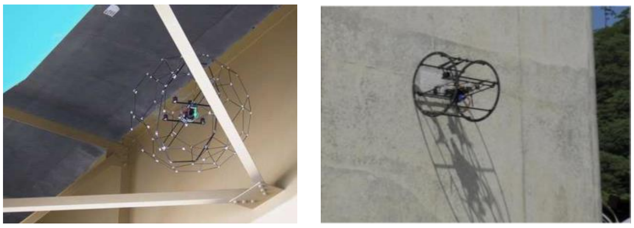
When we inspect a bridge with a UAV, sometimes we have to inspect in a narrow space or to inspect a certain small area more specifically. In that case, a specially designed UAV is more appropriate than an ordinary UAV. There are already several UAVs specially designed for that purpose. Fig. 4(a) shows a specially designed UAV which has a carbon fiber skeleton with a spherical exoskeleton for protecting the UAV and a UAV having two wheels which can climb and run on the bridge surface, respectively (Salaan *et al.* 2018, Yamada *et al.* 2017). Moreover, Myeong and Myung (2019) have developed a different approach which is the posture-changing UAV using a tilt-rotor mechanism as shown in Fig. 4(b).

Myeong (2019) proposed another attachment-type UAV. It has a rotary arm so that it can address disadvantages in terms of energy efficiency and impact in attaching and detaching processes of the existing attachment-type UAV shown in Fig. 4(b). Fig. 5(a) shows its detail view. The outdoor experiment has successfully proceeded on a bridge as shown in Fig. 5(b).

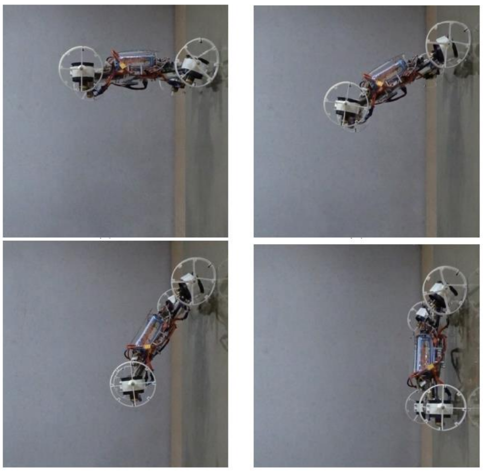
3.2 Image data acquisition related challenges

As seen in Table 1, the second and third major challenges are mainly related to the post-inspection phase. Fig. 5 shows a detailed procedure in the post-inspection phase. As shown in the figure, the second major challenge is to check for the missing part in the inspection area from the acquired images and to evaluate the quality of the image data obtained in the inspection phase and, if necessary, improve the quality. The next step is to identify the damage, which is related to the third major challenge.

In the previous relevant studies, the technology to evaluate the quality of images acquired by UAV or to check for the missing part in the inspection area from acquired images has not been taken into consideration even though they are crucial processes for real implementation of bridge inspection. In addition, it is very important to know the locations of the captured images on the whole inspection area and more precisely the location of the damage in the image.

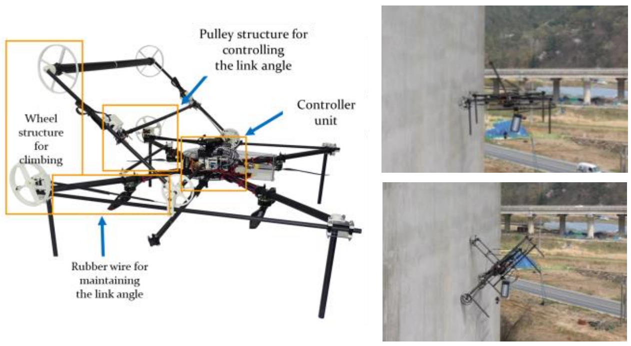


(a) Specially designed UAVs (Salaan *et al.* 2018, Yamada *et al.* 2017)



(b) An attachment-type UAV using a tilt-rotor mechanism (Myeong and Myung 2019)

Fig. 4 Specially designed UAVs for detailed inspection



(a) Detail view of the UAV (b) Field test

Fig. 5 An attachment-type UAV having an auxiliary arm (Myeong 2019)

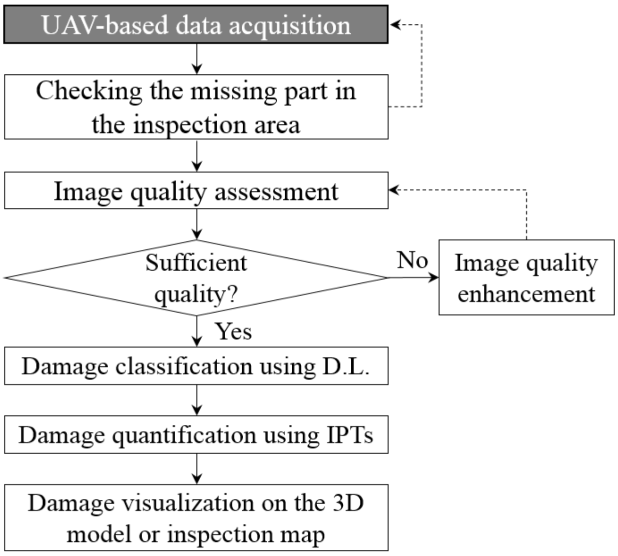


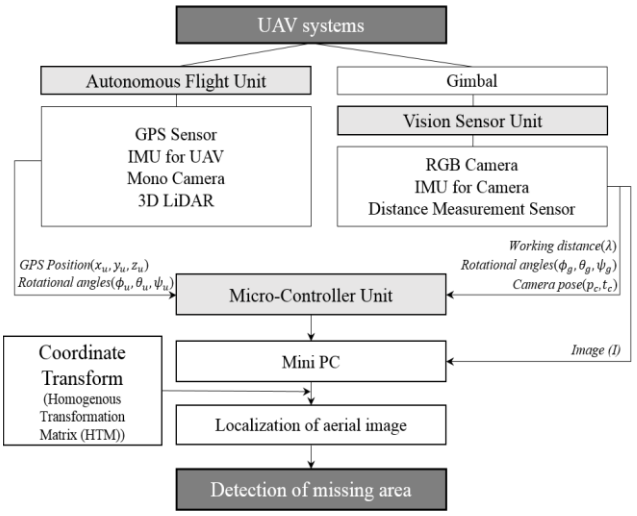
Fig. 6 The detailed process in the post-inspection phase

There is a little review of this issue as well. In this section, technical solutions are presented for addressing these challenges.

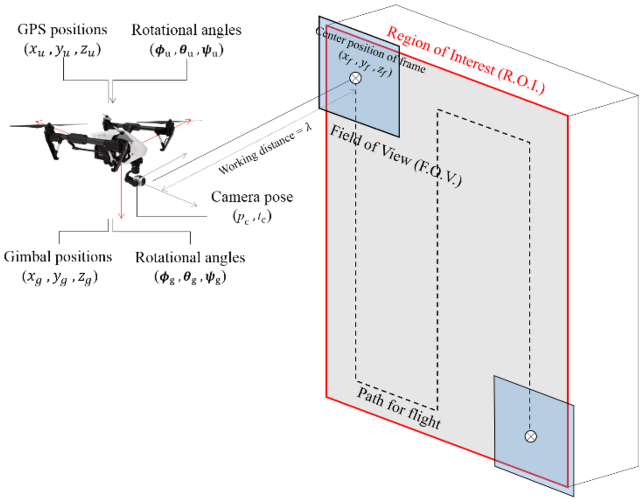
3.2.1 Possibility of the missing part in the inspection area from the acquired image data

During a bridge inspection using a UAV, the UAV takes still shots or videos along the predetermined flight path in a plurality of disturbances. Therefore, it cannot be guaranteed that the captured images cover the entire inspection area completely, that is, without missing parts. In principle, if there is a missing part, the part must be inspected by the UAV again.

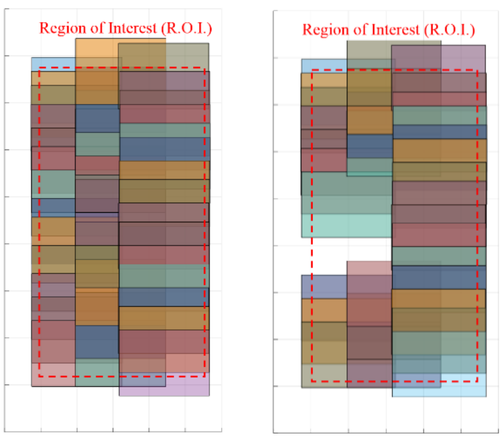
To address this challenge, a new strategy is proposed as shown in Fig. 7. Fig. 7(a) represents the schematic diagram of the proposed strategy. The position and posture information of the UAV (i.e., x_u, y_u, z_u, ϕ_u, θ_u, and ψ_u) are received from the autonomous flight unit. At the same time, the posture information of the imaging device placed on the gimbal (ϕ_g, θ_g, ψ_g, p_c, and t_c) and the distance between the imaging device and the inspection area (λ) are obtained from the vision sensor unit and the distance measurement sensor, respectively. In addition, the system is operated in such a way that images taken at the same time are integrated and stored. And, the localization of the aerial image is made through a coordinate transformation based on all the information calculated from the preceding steps. In other words, the location of the image frame on the inspection area can be estimated. Finally, the missing part in the inspection area can be checked by considering all the image frames. Fig. 7(b) illustrates the operating principle of the proposed strategy. First, the region of interest (ROI) is set, and then the UAV acquires the image data as it travels along the given path. As shown in the figure, the position of the image frame can be estimated from the sensors mounted on the UAV. As shown in Fig. 7(c), it is easy to check whether there is a missing area or not because the center of the specific image frame and the field of view (FOV) can be simply calculated from the given information.



(a) The schematic diagram of the proposed strategy



(b) Operating principle of the proposed strategy



(c) Two simple examples of the proposed strategy (the case of no missing part (left) and the case having a missing part (right))

Fig. 7 The proposed strategy to check the missing part in the inspection area from the acquired image data

3.2.2 Uncertainty of the Image quality

The quality of acquired images is influenced by various environmental factors such as strong winds, turbulence, and sudden operator inputs as well as pilot's skill and stability of the UAV (Sieberth *et al.* 2016). The quality issue that occurs mainly in UAV's images is motion blur due to UAV's vibration or insufficient shutter speed. Image blurring due to motion blur may result in undetected or inaccurate results in the step of quantifying the damage since the blurred image and associated pixel information is lost. In other words, in UAV-based bridge inspection, the image quality is directly related to the quantification results of damage information, and a sufficient level of the image quality must be ensured in order to obtain objective and reliable results. Therefore, a quality measure is needed to evaluate the quality of many images acquired from the UAV for bridge inspection. If the image quality is insufficient, a process of canceling the effect of motion blur through the quality enhancement step is required.

In general, various measures such as Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Structural Similarity Metric (SSIM), and Information Fidelity Criteria are used as indicators to evaluate the image quality. However, the above-mentioned quality measure is a measure of relative quality such as color, saturation and brightness through comparison with the original image, and a different quality measure is needed when the reference image cannot be used.

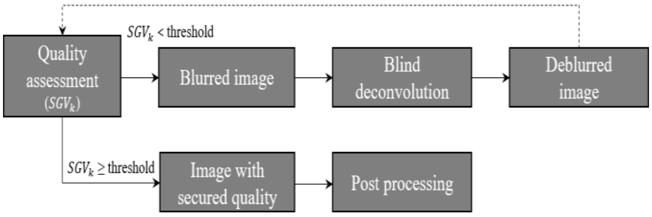
The parameter associated with image blur is image sharpness, and the value of this sharpness can be calculated through the gradient between pixels in the image. The greater the degree of image blur, the larger the image sharpness value, which indicates that the change in gray intensity between pixels is greater. The image quality measure SGV (sum of gray-intensity variation) that can measure the degree of motion blur based on the characteristics of the image parameter is as follows

$$SGV_k = \sum_{i=1}^{M}\sum_{j=1}^{N}\frac{\sqrt{\left(G_k(i,j)-G_k(i,j+1)\right)^2+\left(G_k(i,j)-G_k(i+1,j)\right)^2}}{\sqrt{M^2+N^2}} \quad (1)$$

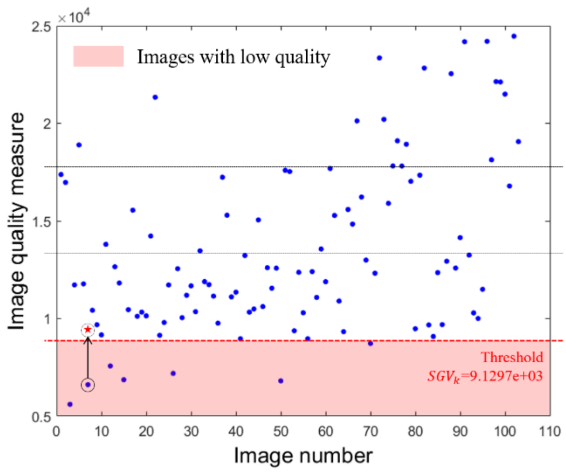
where SGV_k represents the quality measure of the k-th image; M represents the number of horizontal pixels in the image; N represents the number of vertical pixels in the image; G_k represents the gray-intensity function of the k-th image. Using the proposed SGV_k, the quality assessment of the no-reference image is possible and it is possible to classify the images with relatively low quality. Fig. 8(a) describes the flow of image quality assessment and enhancement according to the value of SGV_k. Fig. 8(b) shows the result of evaluation using the proposed quality measure for 103 sample images of a concrete bridge. As a result of applying to a total of 103 images, the SGV_k value averaged 1.3607e+04 and the standard deviation 0.4477e+04. To determine images with sufficient quality, the threshold value was calculated as 9.1297e+03, which is the mean of the image minus the standard deviation. Using the calculated threshold value, 7 out of 103 images were classified as the low quality images due to the motion blur. That is, 7 images are classified as needing quality enhancement. Fig. 8(c) shows the result of blind deconvolution for a specific image with a lower threshold value $\geq SGV_k$. The SGV_k value of the image prior to the enhancement step is 3.2625e+03, which is lower than the threshold value and classified as a low quality image. However, through deconvolution, the SGV_k value is improved to 9.7249e+03 higher than the threshold value.

3.3 Damage identification related challenges

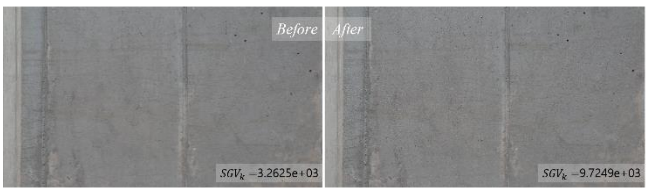
Once enough quality image data have been acquired for the entire inspection area through the techniques described in the previous section, the damage identification step can be carried out. In this way, the amount of image data covering the entire inspection area is huge, so it is very important to solve such data inundation issue well. Suppose a bottom flange of a box-girder bridge of 10 m by 30 m is acquired with FOV of 1 m by 1 m and a 4k image with an overlap ratio of 50%. In this case, about 1,200 images will be acquired, and if it is expanded to the whole bridge, the total number of images will be several tens of thousands.



(a) Flow of image quality assessment and enhancement



(b) Values of image quality measure



(c) Results of de-blur algorithm to low quality image

Fig. 8 Image quality assessment and enhancement strategy and its results

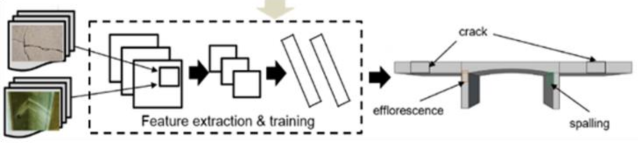
Furthermore, because of the wide variety of damage to be identified (e.g., cracks, spalling, efflorescence, exposed rebar, etc.), proper techniques are needed to detect all of these various types of damage. Under these conditions, if damage identification is performed using existing image processing techniques, it may not be possible to apply it because of the long processing time. In this section, solutions for addressing two challenges related to damage identification are presented and discussed.

3.3.1 Damage detection from a huge amount of image data

As mentioned previously, a huge amount of image data (i.e., the data inundation issue) is one of the major obstacles to bridge inspection using UAV equipped with imaging devices such as vision cameras. In addition, a complicated process of classifying various types of damage and quantifying each damage is required, which is almost impossible with conventional image processing techniques. In order to solve these problems, damage detection should not be done manually but should proceed as much as possible in an automated manner.

Many specific studies focusing on damage identification based on digital images have been carried out during the past decade. Digital image processing techniques used to be used a lot, but deep learning algorithms are getting a lot more attention these days. There are many previous relevant studies and detailed information on the computer vision-based damage detection can be found in Spencer *et al.* (2019). Jahanshahi et al. did pioneering work in automatic image-based defect detection of bridge structures about ten years ago (2009, 2013). And, Yeum and Dyke developed vision-based crack detection for automated inspection of bridge structures (2015). In 2017, Hoskere et al. proposed a novel deep learning algorithm for general damage identification of six different types of damage (2017) and they showed the feasibility of their method, while much work is required for real-world application.

(a) Image acquisition using UAVs



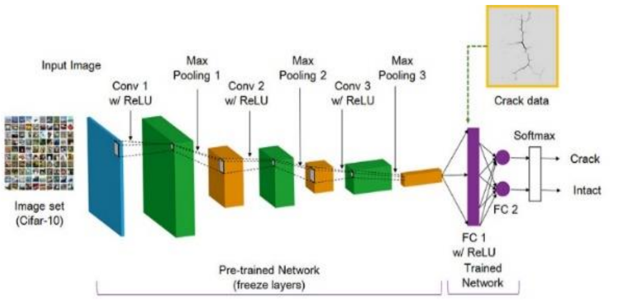
(b) Damage classification and localization using *deep learning*

(c) Damage quantification using *digital image processing*

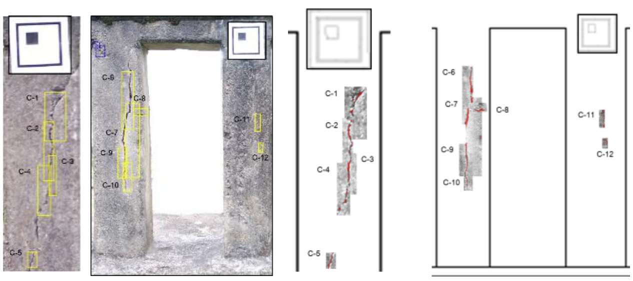
Fig. 9 Typical procedure of UAV-based damage identification of a bridge using deep learning algorithms (Kim *et al.* 2018)

In UAV-based bridge inspection, it is one of the most important tasks to detect and classify the damage from the images obtained from the UAV. In recent years, the deep learning based approach has received considerable research attention due to its several attractive features. Fig. 9 shows a typical procedure of UAV-based damage identification of a bridge using deep learning algorithms.

Here are two application examples. The first case is to identify the damage by applying the deep learning method with the images obtained by the UAV-based inspection of the old concrete bridge. In this case, the region-based convolutional neural network (R-CNN) algorithm was used to do both image classification and localization. Contrary to the CNN based on a sliding window, the R-CNN was used as the object detector, and transfer learning with a rich dataset was used in the deep learning architecture. 50,000 training images from the Cifar-10 dataset were pre-trained using CNN. Then, the pre-trained network was fine-tuned for crack detection using the 384 collected crack images. In object detection, various cracks could be detected by training the deep learning network with a small number of crack images. The detected cracks were cropped and quantified by image processing. Finally, the identified cracks were automatically visualized on the inspection map using matching of their locations. In this study, a field test to apply crack identification techniques in the aging bridge was conducted. As a result, the performance of the proposed technique has been validated to effectively inspect cracks, and the UAV-based bridge inspection system could be considered as one of the promising strategies.

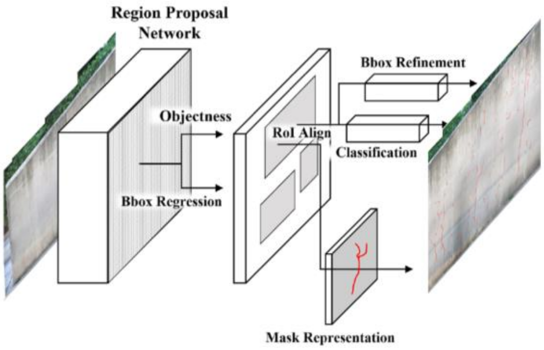


(a) Overall architecture of R-CNN algorithm

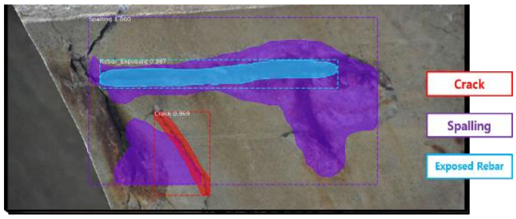


(b) Results of crack detection

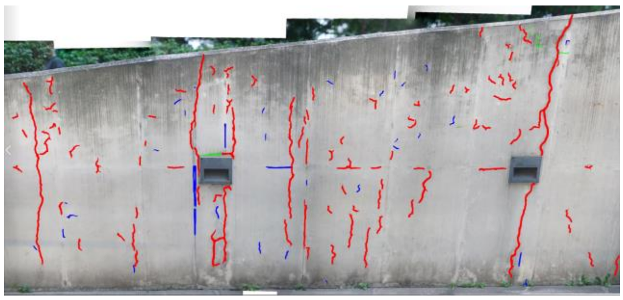
Fig. 10 UAV-based damage identification using the R-CNN algorithm (Kim *et al.* 2018)



(a) Overall architecture of Mask R-CNN)



(b) Damage-type classification and localization



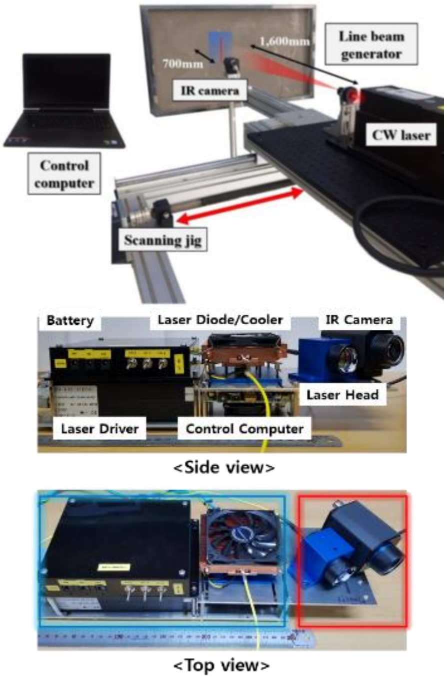
(c) Detection results displayed in the form of confusion matrix (red: true positive, green: false negative, blue: false positive)

Fig. 11 Damage identification using the Mask R-CNN algorithm (Kim and Cho 2019)

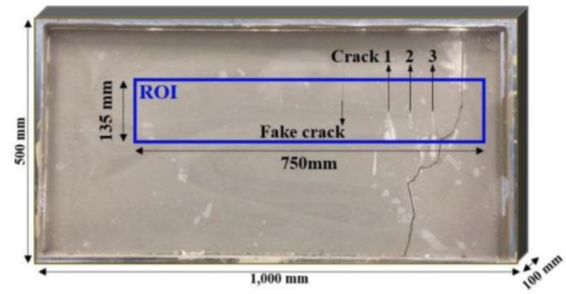
Fig. 10 shows the overall architecture of the R-CNN algorithm used in this study and the results of crack detection. A more detailed explanation of this example can be found in Kim *et al.* (2018).

The next case is about the mask and region-based CNN (i.e., Mask R-CNN) algorithm. A Mask R-CNN is a 3-step deep learning model developed for detecting and classifying objects in an image and segmenting the detected objects at the pixel level, which has succeeded in classifying image databases with high accuracy. Kim and Cho (2019) used this algorithm for detecting and classifying objects in an image and segmenting the detect objects at the pixel level. Fig. 10 represents the overall architecture of Mask R-CNN, the damage-type classification and localization example, and the detection results displayed in the form of the confusion matrix.

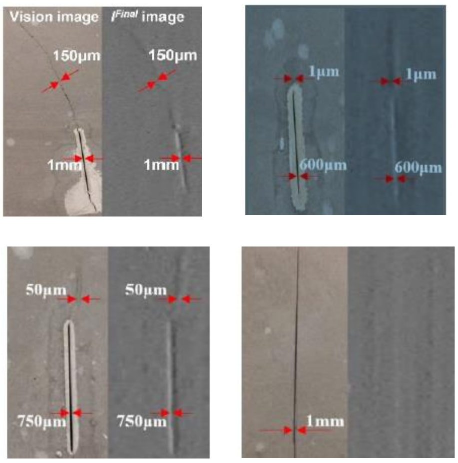
In their work (Kim and Cho 2019), Mask R-CNN is pre-trained with a COCO dataset and then trained for crack detection using 1,102 crack regions masked on 376 concrete



(a) Experimental setup and a miniaturized system for UAV



(b) Concrete specimen with cracks and ROI used in the test



(c) Comparison between the vision and IR images (crack 1, crack 2, crack 3, and fake crack)

Fig. 12 Hybrid scanning system combining vision and IR cameras for minimizing false alarm (Jang and An 2018)

images. The trained Mask R-CNN model is tested on the images taken from a real concrete wall with 453 cracks whose widths range from less than 0.1 mm to 1.0 mm. The trained model successfully detects most of the cracks 0.3 mm or wider. Quantification of the cracks was then carried out using several image-processing operations on 10 randomly selected crack masks. Cracks with widths of 0.3 mm or more are quantified successfully with errors less than 0.1 mm, whereas cracks less than 0.3 mm widths show relatively larger error due to the limitation of image resolution. A more detailed description of this example can be found in Kim and Cho (2019).

3.3.2 False alarm

The final challenge is the false alarm problem. It is widely known that a false alarm cannot be avoided with a single camera. Since captured images from a vision camera are mainly used for crack evaluation, there is a high possibility of false alarms due to various factors such as camera angle change, illumination condition, and foreign matter on the surface of the structure. Especially, due to the limitation of camera FOV, it is difficult to evaluate cracks of large structures such as bridges. In order to overcome the limitations of the existing vision camera-based system, the hybrid image scanning system combining vision image and laser thermal image has been developed by Jang and An (2018). Their system consists of a line shape continuous-wave laser source, an infrared (IR) camera, a control computer, and a scanning jig. The proposed system is able to rapidly and precisely evaluate multiple cracks, especially in a large-scale concrete structure. In particular, timely- and spatially-varying images are transformed into stationary images for precise crack evaluation by developing a time-spatial-integrated coordinate transform algorithm.

Fig. 12(a) shows the experimental setup in a laboratory environment and a miniaturized system for mounting on the UAV. Fig. 12(b) describes the concrete specimen with various-size cracks including a fake crack and ROI used in the test. Fig. 12(c) shows the comparison results between the vision and IR images. As seen from the figures, in the case of vision camera alone, a fake crack cannot be differentiated from actual cracks. On the other hand, by using the proposed system, it can be clearly identified. Thus, it is verified that the proposed system can improve the crack detection ability and minimize the false alarm.

4. Conclusions

This paper investigated bridge inspection and condition assessment using UAVs from a practical perspective. To this end, the three major challenges were first identified by examining the typical UAV-based bridge inspection procedure consisting of the pre-inspection, inspection, and post-inspection phases. And then, the corresponding solutions were presented and discussed as follows: the graph-based UAV localization algorithm for estimating the location of the UAV in the GPS denied environment, a customized UAV suitable for bridge inspection to enhance the UAV performance, and the strategies to check the missing part in the inspection area and to assess the quality of the captured image data for dealing with the data acquisition challenges. In addition, automated damage identification approaches using deep learning models for effectively detecting various damage types from a huge amount of image data was presented, and a hybrid scanning system consisting of vision and IR cameras for minimizing false alarms was described. Based on the discussion of the major challenges and their solutions, the detailed bridge safety diagnosis, as well as the routine inspection, can be effectively performed using UAVs in the real world in the near future, provided that the technologies presented here are fully developed. Thus, it can be concluded that a paradigm shift of bridge inspection and condition assessment will be realized mainly by UAV-centric advanced technologies together with deep learning algorithms from time-consuming, costly, manual, subjective, and dangerous approaches to rapid, cost-effective, automated, objective, and much safer approaches.

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References

Akbar, M.A., Qidwai, U. and Jahanshahi, M.R. (2019), “An evaluation of image-based structural health monitoring using integrated unmanned aerial vehicle platform”, *Struct. Control Health Monit.,* **26**, e2276. DOI: 10.1002/stc.2276.

American Society for Civil Engineers (ASCE) (2017), https://www.infrastructurereportcard.org/.

Brooks, C., Dobson, R.J., Banach, D.M., Dean, D., Oommen, T., Wolf, R.E. and Hart, B. (2015), “Evaluating the use of unmanned aerial vehicles for transportation purposes (No. RC-1616)”, Michigan Tech Research Institute, Ann Arbor. https://www.micigan.gov/documents/mdot/RC1616_Part_C_48 8515_7.pdf

Chan, B., Guan, H., Jo, J. and Blumenstein, M. (2015), “Towards UAV-based bridge inspection systems: a review and an application perspective”, *Struct. Monit. Maint.*, **2**(3), 283-300. https://doi.org/10.12989/smm.2015.2.3.283.

Chen, S., Linh, T.-H., Laefer, D. and Mangina, E. (2018), “Automated bridge deck evaluation through UAV derived point cloud”, *Proceedings of the 2018 Civil Engineering Research in Ireland Conference*, Dublin, August.

Chen, S., Laefer, D.F., Mangina, E., Zolanvari, S.M.I. and Byrne, J. (2019), “UAV bridge inspection through evaluated 3D reconstructions”, *J. Bridge Eng*., **24**(4), 05019001. DOI: 10.1061/(ASCE)BE.1943-5592.0001343.

Cho, S. and Lee, S. (2009), “Fast Motion Deblurring”, *ACM Trans. Graph.*, **28**(5), Article 145. DOI: 10.1145/1618452.1618491.

Darby, P., Hollermann, W. and Miller, J. (2019), “Exploring the potential utility of unmanned aerial vehicles for practical bridge inspection in Louisiana”, *Proceedings of the MATEC Web of Conferences*, **271**, 01001. DOI: 10.1051/matecconf/ 201927101001.

Delgado, J.P., Soria, P.R., Arrue B.C. and Ollero, A. (2017), “Bridge mapping for inspection using an UAV assisted by a total station”, *Proceedings of the ROBOT 2017: Third Iberian Robotics Conference*, 309-319. DOI: 10.1007/978-3-319-70836-2_26.

Dorafshan, S. and Maguire, M. (2018), “Bridge inspection: human performance, unmanned aerial systems and automation”, *J. Civil Struct. Health Monit.*, **8**, 443-476. DOI: 10.1007/s13349-018-0285-4.

Duque, L. (2017), “UAV-based bridge inspection and computational simulations”, Theses and Dissertations, 2159, South Dakota State University, South Dakota.

Eschmann, C., Kuo, C.M., Kuo, C.H. and Boller, C. (2013), “High-resolution multisensor infrastructure inspection with unmanned aircraft systems”, *Proceedings of the International Archives of the Phtogrammetry, Remote Sensing and Spatial Information Sciences*, Rostock, Germany, September.

Fujino, Y. and Takada, T. (2008), “Risk assessment, management and monitoring of infrastructure systems”, *Department of Civil Engineering Report*, University of Tokyo, Tokyo.

Hallermann, N. and Morgenthal, G. (2014), “Visual inspection strategies for large bridges using Unmanned Aerial Vehicles (UAV)”, *Proceedings of the 7th International Conference on Bridge Maintenance, Safety and Management (IABMAS 2014),* Shanghai, July.

Han, K., Lin, J. and Golparvar-Fard, M. (2015), “A formalism for utilization of autonomous vision-based systems and integrate project models for construction progress monitoring”, *Proceedings of the Conference on Autonomous and Robotic Construction of Infrastructure*, Ames, IA, USA, June.

Hoskere, V., Narazaki, Y., Hoang, T.A. and Spencer, B.F. Jr. (2017), “Vision-based structural inspection using multiscale deep convolutional neural networks”, *Proceedings of the 3rd Huixian International Forum on Earthquake Engineering for Young Researchers*, Urbana, IL, USA, August.

Irizarry, J. and Johnson, E.N. (2014), “Feasibility study to determine the economic and operational benefits of utilizing unmanned aerial vehicles (UAVs)”, FHWA-GA-1H-12-38. Georgia Institute of Technology. https://smartech.gatech.edu/handle/1853/ 52810?show=full.

Jahanshahi, M.R., Kelly, J.S., Masri, S.F. and Sukhatme, G.S. (2009), “A survey and evaluation of promising approaches for automatic image-based defect detection of bridge structures”, *Struct. Infrastruct. Eng*., **5**(6), 455-486. DOI: 10.1080/15732470801945930.

Jahanshahi, M.R. and Masri, S.F. (2013), “A new methodology for non-contact accurate crack width measurement through photogrammetry for automated structural safety evaluation”, *Smart Mater. Struct.*, **22**(3), 035019. DOI: 10.1088/0964-1726/22/3/035019.

Jang, K. and An, Y.K. (2018), “Multiple crack evaluation on concrete using a line laser thermography scanning system”, *Smart Struct. Syst.,* **22**(2), 201-207. https://doi.org/10.12989/sss.2018.22.2.201.

Jordan, S., Moore, J., Hovet, S. Box, J., Perry, J., Kirsche, K., Lewis, D. and Tse, Z.T.H. (2018), “State-of-the-art technologies for UAV inspections”, *IET Radar Sonar Nav.*, **12**(2), 151-164. DOI: 10.1049/iet-rsn.2017.0251.

Jung, S., Song, S., Kim, S., Park, J., Her, J., Roh, K. and Myung,

H. (2019), "Toward autonomous bridge inspection: a framework and experimental results", *Proceedings of the 16th International Conference on Ubiquitous Robots (UR)*, Jeju, Korea, June.

Khaloo, A., Lattanzi, D., Cunningham, K., Dell'Andrea, R. and Riley, M. (2018), ″Unmanned aerial vehicle inspection of the Placer River Trail Bridge through image-based 3D modelling", *Struct. Infrastruct. Eng.,* **14**(1), 124-136. DOI: 10.1080/15732479.2017.1330891.

Kim, H.J., Lee, J.H., Ahn, E.J., Cho, S.J., Shin, M.S. and Sim, S.H. (2017), "Concrete crack identification using a UAV incorporating hybrid image processing", *Sensors*, **17**, 2052. DOI: 10.3390/s17092052.

Kim, B. and Cho, S. (2019), "Image-based concrete crack assessment using mask and region-based convolutional neural network", *Struct. Control Health Monit.*, DOI: 10.1002/stc.2381.

Lee, Y., Kim, B. and Cho, S. (2018), "Image-based spalling detection of concrete structures incorporating deep learning", *Proceedings of the 7th World Conference on Structural Control and Monitoring*, Qingdao, China, July.

Lovelace, B. and Zink, J. (2015), "Unmanned Aerial Vehicle Bridge Inspection Demonstration Project", Report No. MN/RC 2015-40, Minnesota Department of Transportation Research Services & Library, St. Paul, MN.

Moller, S. (2008), "CALTRANS Bridge inspection aerial robot", CA08-0182, Final report. Division of research and innovation, California Department of Transportation. Scaramento. www.dot.ca.gov/newtech/researchreports/reports/2008/08-0182.pdf

Morgenthal, G. Hallermann, N., Kersten, J., Taraben, J., Debus, P., Helmrich, M. and Redehorst, V. (2019), "Framework for automated UAS-based structural condition assessment of bridges", *Automat. Constr.*, **97**, 77-95. DOI: 10.1016/j.autcon.2018.10.006.

Munguia, R., Urzua, S., Bolea, Y. and Grau, A. (2016), "Vision-based SLAM system for unmanned aerial vehicles", *Sensors*, **16**(3), 372. DOI: 10.3390/s16030372.

Myeong, W.C. and Myung, H. (2019), "Development of a wall-climbing drone capable of vertical soft landing using a tilt-rotor mechanism", *IEEE Access*, **7**(1), 4868-4879. DOI: 10.1109/ACCESS.2018.2889686.

Myeong, W.C. (2019), "Development of a wall-climbing UAV using tilt-rotor and an auxiliary arm", Ph.D. Dissertation, KAIST, Daejeon, Korea.

Otero, L.D., Gagliardo, N., Dalli, D., Huang, W.H. and Cosentino, P. (2015), "Proof of concept for using unmanned aerial vehicles for high mast pole and bridge inspections", (No. BDV28 TWO977-02). Florida Institute of Technology. https://rosap.ntl.bts.gov/view/dot/29176/dot_29176_DS1.pdf

Pan, J., Sun, D., Pfister, H. and Yang, M.H. (2016), "Blind image dublurring using dark channel prior", *Proceedings of the 2016 IEEE Conference on Computer Vision and Pattern Recognition* (CVPR), Las Vegas, NV, USA, June.

Pereira, F.C. and Pereira, C.E. (2015), "Embedded image processing systems for automatic recognition of cracks using UAVs", *IFAC-PapersOnLine*, **48**, 16-21. DOI: 10.1016/j.ifacol.2015.08.101.

Sabatini, R., Gardi, A. and Richardson, M.A. (2014), "LIDAR obstacle warning and avoidance system for unmanned aircraft", *Int. J. Comput. Syst. Eng*. **8**, 711–722. DOI: 10.1016/j.ast.2016.05.020.

Sacks, R., Kedar, A., Borrmann, A., Ma, L., Brilakis, I., Huthwohl, P., Daum, S., Kattel, U., Yosef, R., Liebich, T., Barutch, B.E. and Muhic, S. (2018), "SeeBridge as next generation bridge inspection: overview, information delivery manual and model view definition", *Automat. Constr.*, **90**, 134-145. DOI: 10.1016/j.autcon.2018.02.033.

Salaan, C.J.O., Okada, Y., Mizutani, S., Ishii, T., Koura, K., Ohno, K. and Tadokoro, S. (2018), "Close visual bridge inspection using a UAV with a passive rotating spherical shell", *J. Field Robotics*, **35**, 850-867. DOI: 10.1002/rob.21781.

Sieberth, T., Wackrow, R. and Chandler, J.H. (2016), "Automatic detection of blurred images in UAV image sets", *ISPRS J Photogramm*, **122**, 1-16. DOI: 10.1016/j.isprsjprs.2016.09.010.

Song, S., Jung, S., Kim, H. and Myung, H. (2018), "A method for mapping and localization of quadrotors for inspection under bridges using camera and 3D-LiDAR", *Proceedings of the 7th Asia-Pacific Workshop on Structural Health Monitoring*, Hong Kong SAR, P.R. China. November.

Spencer, Jr., B.F., Hoskere, V. and Narazaki, Y. (2019), "Advances in computer vision-based civil infrastructure inspection and monitoring", *J. Eng.*, **5**, 199-222. DOI: 10.1016/j.eng.2018.11.030.

Wells, J. and Lovelace, B. (2017), "Unmanned Aircraft System Bridge Inspection Demonstration Project Phase II", Report No. MN/RC 2017-18, Minnesota Department of Transportation Research Services & Library, St. Paul, MN.

Wu, L. (2015), "Applications of computer vision technology of automated crack detection and quantification for the inspection of civil infrastructure systems", Ph.D. Dissertation, University of Central Florida.

Yamada, M., Nakao, M., Hada, Y. and Sawasaki, N. (2017), "Development and field test of novel two-wheeled UAV for bridge inspections", *Proceedings of the 2017 International Conference on Unmanned Aircraft Systems (ICUAS)*, Miami, FL, USA. June.

Yeum, C.M. and Dyke, S.J. (2015), "Vision-based automated crack detection for bridge inspection", *Comput. Civ. Infrastruct. Eng.*, **30**(10), 759-770. DOI: 10.1111/mice.12141.