Masonry Crack Detection
Application of an Unmanned Aerial Vehicle

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ABSTRACT

The predominant method for infrastructure evaluation is visual inspection. The large number and scale of inspections often make it difficult to catalog the location, size, and severity of the identified damage. Several nondestructive methods can be used to detect cracks, such as acoustic emission and ultrasound, but they require the installation of many sensors, typically involve measurements in a predetermined area, and often require post-processing. Though image-based crack detection is limited to inspecting surface cracks, it has advantages including speed, repeatability, and large area coverage. Furthermore, the use of image stitching can provide a comprehensive assessment of the health of the entire structure. This method could also be applied using an unmanned aerial vehicle (UAV). This paper discusses major challenges in automated crack detection and implementation on UAVs.

INTRODUCTION

Congress passed a bill in 2012 that allows drones weighing less than fifty-five pounds to fly in the United States after May 2013. In addition, first response agencies are currently allowed to use UAVs with weights less than 4.4 pounds to support them in their work (Klotz, 2012). In this context, Federal Aviation Administration (FAA) is required to allow access for all drones by 2015 (Elias, 2012). While FAA is currently defining the requirements and rules for the use of UAVs (Klotz, 2012), relevant research is being conducted in academia.

Of the various techniques used for infrastructure inspection, visual inspection by trained personnel is the primary method of inspection (C Eschmann, KUO, KUO, and Boller, 2012; Laefer, Gannon, and Deely, 2010). Masonry building inspection is often conducted from the ground making it difficult to obtain consistent results with different inspectors (Laefer et al., 2010). The results of the inspections must be well documented and this can also vary with the inspector (Laefer et al., 2010). The same problems exist with images taken from the ground. The main advantage is that they

can be viewed later by more people to make a decision, however typical damage is often local which makes it difficult to determine where the picture was taken with respect to the structure so that damage can be located (Laefer et al., 2010).

The main goal of this research is to utilize a UAV for surface crack detection on masonry surfaces. An algorithm is here presented that includes quantitative measurements of cracks, as well as global positioning system (GPS) data to locate the detected crack on the structure.

BACKGROUND

Image Processing and Crack Detection. Almost every image processing technique for identification starts with some sort of image segmentation. The use of edge detection to identify cracks has been extensively studied. The Sobel method, which involves using a gradient in the x and y directions respectively for each pixel in the image, was analyzed and improved for the purpose of pavement cracks by Yongxia (Yongxia, Guoqiang, and Chuncheng, 2008). Yongxia also analyzed the Otsu method, which classifies the image parts into background and foreground and computes the variance to find the best threshold to minimize the variance (Yongxia et al., 2008). The Prewitt method for edge detection was explored by Hu (Dongna, Tian, Hengxiang, Shibo, and Xiujin, 2012). The method used polynomials to find the path and eliminated points that were isolated from the identified cracks making a significant improvement over basic Prewitt edge detection.

The fractal method performed better than the Sobel and Otsu methods in both areas and was able to be used real-time to analyze pavement surface cracks (Yongxia et al., 2008), but this algorithm does not measure the cracks it detects. It was demonstrated that the fractal approach also can model the extent of the damage using a damage index (Farhidzadeh, Dehghan-Niri, Moustafa, Salamone, and Whittaker, 2013). This method takes into account the crack pattern to classify damage.

The percolation method takes advantage of the brightness of the pixels, but analyzes each one individually and only keeps the pixels which are darker than the current pixel (Yamaguchi and Hashimoto, 2010). This approach simply segments the image by color to identify cracks. Pothole detection using a ground vehicle have been successfully completed by image segmentation (Koch and Brilakis, 2011). The segmentation was followed by shape and texture extraction to determine where the potholes were located.

Tensor voting has also been used to determine the most likely crack path (Zou, Cao, Li, Mao, and Wang, 2012). This approach used a minimum spanning tree of known crack points to determine the most likely locations of the cracks. The method does not directly measure cracks, but it gives a good representation of where the cracks are located in each image even when there is a significant amount of noise in the image.

Many problems with image segmentation have to do with differing lighting conditions throughout the images such as shadows. It has been shown that for pavement images, shadows can be corrected and the image can be reconstructed to achieve more accurate segmentation (Adu-Gyamfi, Okine, Garateguy, Carrillo, and Arce, 2012). Zou et al. (2012) utilized shadow removal in conjunction with tensor voting for crack identification.

Unmanned Aerial Vehicle. Fixed Wing Inspection. The use of an aerial vehicle for inspection has been investigated, but currently the main applications are for large, "linear" infrastructure such as roadways or power lines. To date, most of the successful inspections using a fixed wing aerial vehicle to perform inspection on a roadway or power lines are manned flights, but UAVs are becoming increasingly more popular. The main challenge for this type of inspection is the distance that must be maintained from the target to achieve good detection sensitivity, but high resolution cameras have made it possible to obtain images of cracks less than one inch in width (Chen, Rice, Boyle, and Hauser, 2011). Like all visual inspection using photographs, shadows and objects obstructing the view are a problem (Chen et al., 2011). Another difficulty with this type of inspection is that the pilot must constantly get feedback from the person taking the images to know what to do (Chen et al., 2011). It is for this reason that research on (mostly copter) UAVs is currently being conducted.

Rotorcraft inspection. A preliminary inspection was completed by Drexel University using a manned helicopter on a long span movable bridge in the Philadelphia region. The ultimate goal is to do the same test using an UAV. Two types of rotor platforms can be used for a UAV: a helicopter and a multirotor system. The main advantage of a helicopter platform is its significantly longer flight time, while its main disadvantage is there is no redundancy for the motor (C. Eschmann, Kuo, Kuo, and Boller, 2013). The main advantage for multicopters is depending on the configuration, there is redundancy for engine failure, but flight time is significantly lower (C. Eschmann et al., 2013). The main issue with using any UAV is the control of the vehicle. Currently, collision avoidance is done by the pilot or a well-defined flight path using a GPS signal (C. Eschmann et al., 2013). Metni and Hamel showed that a visual based control has the potential to keep a helicopter stable during an inspection, as well as proved that measurements of cracks were possible using the UAV (Metni and Hamel, 2007).

Masonry Crack Detection with a UAV. An unmanned multicopter is a suitable option for inspecting masonry buildings because of its vertical takeoff and landing capabilities, redundancy of engines, and its small, lightweight design (Eschmann et al., 2012; Eschmann et al., 2013). Preliminary crack detection using a UAV has mostly been limited to edge detection techniques and color (Eschmann et al., 2012; Metni and Hamel, 2007). Eschmann used an octocopter to stitch together the side of a building and used edge detection to identify cracks in the millimeter range (Eschmann et al., 2012). Using the same approach, a 3D model of the building was constructed by essentially pasting the image stitching results on all sides of the building onto the faces of the building to construct a 3D view (Eschmann et al., 2013).

PRELIMINARY TESTS

Masonry Wall. Figure 1 shows the experiment used to determine how distance affected the size of detectable crack with a 16MP camera. A sheet of paper with lines of different thicknesses was used for the test. The camera was moved at different

distances from the designed target for each image. This measurement simulated what would be observable in real time by someone flying a drone.
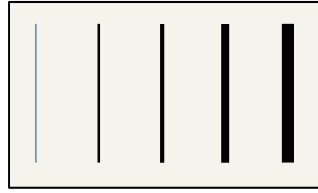
Figure 1. Simulated crack test paper.

Table 1 shows both real-time and post processing results. Using post processing the smallest line with thickness of 0.75 inches could be observed at 40ft from the paper. Without post processing the smallest line that could be viewed was 2mm at 30ft. The crack sizes were predetermined using a ruler before the images were taken.

Table 1. Results of test shown in Figure 1.

Crack Detection Analysis	Distance (ft)	10	15	20	25	30	35	40
Live	Smallest Crack	<0.75	0.75	0.75	1.5	2	N/A	N/A
Post-Processed	Thickness (mm)	0.75	0.75	0.75	0.75	0.75	0.75	0.75

A second test to detect cracks was performed on a masonry wall. Figure 2 shows a visual result using the Parrot AR 2.0 camera. The wall had dimensions of 14ft by 12ft 8in and was loaded vertically (at the top of the wall) and horizontally with increasing cyclically imposed displacement. The highlighted regions in Figure 2 show where the cracks initiated during the fourth test with horizontal displacement amplitude of 0.46 inches. The drone camera at a distance equal to 3ft from the wall had enough resolution to allow the viewer to see the cracks on an I-Pod Touch.
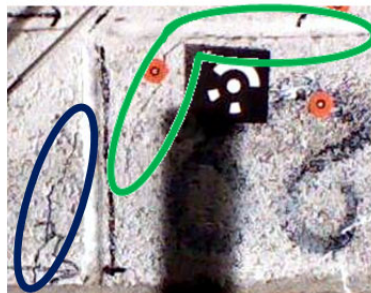
Figure 2. Image from the masonry wall crack test.

The two crack tests demonstrate the feasibility of using a higher resolution camera on a hovering UAV to perform analysis. The cracks detected by a high resolution camera could be subsequently quantified by using post processing.

The markers shown in the image could be used for tracking. In the field, an inspector could apply these markers to a structure during a routine inspection and simply leave them there. This would provide a baseline for the structure as well as provide another method of inspection using a UAV.

Burlington Bristol Bridge. A third test was performed using a manned helicopter to acquire multispectral images. This test resulted in a better understanding of what is required to complete such field measurements. Figure 3a shows a representative

image of the bridge obtained by the helicopter that can be seen flying on top of the bridge in Figure 3b. Samples of the RGB and infrared images obtained from the test are shown in Figure 3c-d. This test showed that even with very experienced pilots, it is difficult to keep a fixed distance from a structure using a helicopter. This type of test, however, could be easier with a UAV because of the constant feedback of a GPS. Specifically, a flight path can be constructed before the flight and GPS feedback will keep the drone within close distance of that. The speed of the path can also be predetermined making it possible to get pictures at regular intervals along the structure.
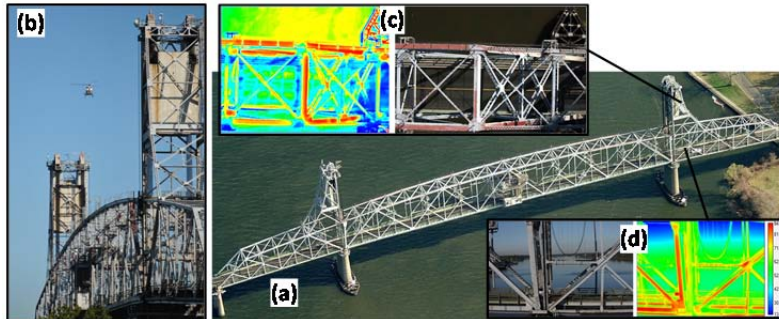
Figure 3. Multispectral aerial imaging of large infrastructure performed by Drexel team: (a) Long span movable bridge; (b) helicopter with multispectral payload collecting images; IR and high resolution RGB images collected from (c) the top and from (d) the side.

ALGORITHMS

Camera Calibration. The goal of the camera calibration is to correct the images for lens distortion. All cameras have lens distortion and this varies for every camera. The choice of aperture, focal length, and shutter speed also affect the pictures. If the properties of the camera are changed, the calibration must be redone to ensure that the calibration corrects for the proper distortion. Figure 4 shows the results for an extreme case of wide angle lens distortion using a calibration algorithm (Bouguet, 2008).
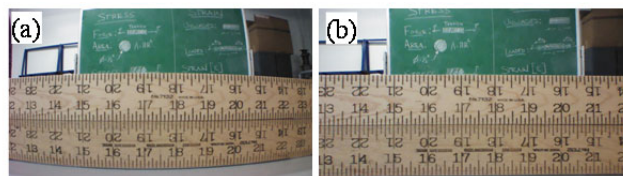
Figure 4. (a) Image with wide angle lens distortion; (b) Same image corrected for lens distortion.

Figure 4(a) was corrected for lens distortion using the multi-plane calibration method. This method uses many pictures taken at different angles to minimize the error between projected points and image positions. The error is a nonlinear function of intrinsic and extrinsic properties as well as radial distortion. The minimization of this error determines a best fit function to describe the lens distortion and correct a set of new images for the same parameters. The calibration was done using an online readily available MATLAB code (Bouguet, 2008).

Homography. Homography is important for setting up a scale and measuring the cracks. There must be a measurement plane with at least 4 points with known distance with respect to each other. This step flattens the image in that plane making the distance per pixel the same throughout the image. An example of the use of this technique is shown in Figure 5. Even for relatively large angles, it is possible to flatten the image onto a plane if the measurements in the picture are accurate.
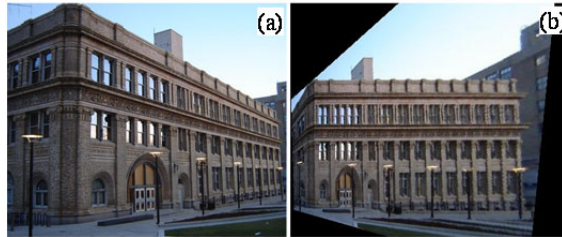
Figure 5. (a) Original image; (b) Image flattened to the front face of the building.

Four known points in the picture need to be used to determine the scale. If the points in the horizontal and vertical directions are at a specified distance apart, the distance is divided by the number of pixels between them to find the distance per pixel in each direction. Ideally, the horizontal and vertical distance per pixel should be the same. If they are not, this must also be accounted to measure the cracks correctly.

Crack Identification. Several approaches were explained in section 0. Edge detection and percolation approaches were used to both identify cracks (shown in Fig. 8a) and fill them in with white pixels when the image is converted to binary. The comparison of the results can eliminate the unwanted noise in the images. Then an algorithm similar to the fly fisher may also be used to ensure that the cracks have a reasonable direction associated with them. Figure 6 shows the results of the application of these algorithms. Part (b) of the figure was achieved by using only color standard deviations on both a global and local scale for the image. It also utilized Hough transform to determine the most likely direction of the cracks. Part (c) is obtained by a built in MATLAB command used to find edges. The percolation approach was added to this algorithm to assist in reducing the noise, but as displayed in part (d), it did not work as well as expected. Once the cracks are identified, features such as roundness, area, perimeter, and other shape properties could be utilized to determine the crack length and width in pixels. Assuming the scale is correct from the previous step, the pixel measurements can also be used to perform distance measurements.
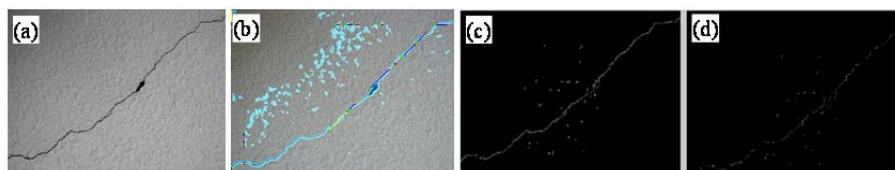
Figure 6. (a) Original image; (b) Results of preliminary algorithm; (c) Results of Prewitt edge detection; (d) Percolation approach after edge detection has been performed.

CHALLENGES

Algorithm. The main challenge for any detection algorithm is noise. Surface roughness, patterns in masonry, edges from windows, doors and ends of the building all cause problems with edge detection. The percolation algorithm also suffers from similar issues. One possible solution is to take baseline pictures and identify an inherent part of the structure that can be filtered out from the results. The major problem with this approach, particularly with brick structures, is that most of the damage initially occurs around these features and therefore would potentially filter out also the sought damage. Another approach is to filter out any edge that is too linear, but that also has the potential to filter out the damage. The algorithm under development currently has too much noise. The problems with edge detection and percolation techniques are all ongoing challenges in image processing and have yet to be fully solved.

UAV. The main challenges to using a UAV are the environmental conditions and flight control. Wind is a huge challenge for this approach. If testing needs to be done between buildings, all of the wind is forced through a smaller area than usual and therefore could set the UAV off course. Another issue is safety. If the wind does take the UAV away from the intended path, it will need to account for this change which currently may be difficult to achieve. The best way to combat the challenge of wind is to only use the UAV when the wind conditions are significantly less than the maximum wind speed the drone can handle. Most small UAVs can reliably fly in winds between 5 and 10mph.

Another important challenge is what happens to the pictures to ensure the cracks are identified. The field of view of the camera, angle at which the UAV and gimbal are oriented, and the GPS location all must be recorded accurately enough to determine what part of the structure is actually in the image. GPS readings can be inaccurate due to interference of structures. A way to limit the effect of interference is to stay farther away from the structure. This would also limit the risk of wind gusts causing the drone to hit the structure during inspection. A system using images, GPS, and gimbal is an improvement over ground based photography because all of the data can be found, but it is still a challenge to use it to locate and identify the cracks and allow for repairs after inspection.

CONCLUSIONS

In this paper, infrastructure evaluation using UAVs was discussed with a focus on masonry crack detection. Several algorithms for crack identification were discussed including edge detection, the percolation approach, the fractal method, and tensor voting. The paper also explained the steps to perform measurements of cracks and showed preliminary results obtained using a crack identification algorithm. In addition, the results of a manned helicopter test using multispectral imaging were presented. Future tests will include the application of a UAV for similar testing. The challenges for small UAV infrastructure evaluation were also explained. UAVs have the potential to significantly change the way infrastructure evaluation will be conducted in the future.

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