Automation in Construction xxx (2016) xxx–xxx

Contents lists available at ScienceDirect

Automation in Construction

journal homepage: www.elsevier.com/locate/autcon

Bridge deck delamination identification from unmanned aerial vehicle infrared imagery

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ARTICLE INFO

Article history:
Received 20 November 2015
Received in revised form 23 June 2016
Accepted 15 August 2016
Available online xxxx

ABSTRACT

The rapid, cost-effective, and non-disruptive assessment of bridge deck condition has emerged as a critical challenge for bridge maintenance. Deck delaminations are a common form of deterioration which has been assessed, historically, through chain-drag techniques and more recently through nondestructive evaluation (NDE) including both acoustic and optical methods. Although NDE methods have proven to be capable to provide information related to the existence of delaminations in bridge decks, many of them are time-consuming, labor-intensive, expensive, while they further require significant disruptions to traffic. In this context, this article demonstrates the capability of unmanned aerial vehicles (UAVs) equipped with both color and infrared cameras to rapidly and effectively detect and estimate the size of regions where subsurface delaminations exist. To achieve this goal, a novel image post-processing algorithm was developed to use such multispectral imagery obtained by a UAV. To evaluate the capabilities of the presented approach, a bridge deck mockup with pre-manufactured defects was tested. The major advantages of the presented approach include its capability to rapidly identify locations where delaminations exist, as well as its potential to automate bridge-deck related damage detection procedures and further guide investigations using other higher accuracy and ground-based approaches.

1. Introduction

Over the last decade there has been increasing recognition of the importance of rapid and cost-effective techniques to assess the condition of bridge decks. In addition to their impact on ride quality, bridge decks serve as a key load-carrying element and the principal environmental protection system for the superstructure. Furthermore, although they represent only a small portion of the initial cost of the bridge, they account for between 50% and 85% of bridge maintenance funds [1]. As a result, tools capable of identifying early deterioration and thus enabling preventive and more cost-effective interventions have potential to significantly reduce the life-cycle cost of bridges.

Currently, there are many different nondestructive evaluation (NDE) methods for identifying damage in bridge decks including impact echo, ground penetrating radar, and several others which require contact with the structure [2]. Some of these techniques have been recently placed on a robotic platform and used simultaneously to achieve a combined evaluation of the bridge deck [3]. Furthermore, non-contact methods for damage identification include multispectral imaging, light detection and ranging, as well as digital image correlation which have been demonstrated to identify both surface and subsurface damage in the case of infrared (IR) imaging [4]. The major benefits of non-contact imagery are the speed at which data can be collected, the full field nature of such data, and the ease of interpreting them when compared to many other methods.

Infrared thermography (IRT) imaging has been used in several NDE applications [5]. For example, infrared images have been used to determine the moisture content in roofs and analyze the performance of wet insulation [6,7]. In addition and along with other NDE methods, IRT has applications is robotic tunnel inspection [8]. Active thermography involves a heat source or mechanical stimulation used as excitation inputs to identify defects and has been demonstrated in aerospace NDE applications primarily involving honeycomb structures [9]. Both active and passive thermography have been shown to identify defects in elements of bridges, such as delaminations in bridge decks [10,11]. Specifically, detection of subsurface defects in concrete structures was based on heat transfer changes in flawed regions detected by temperature gradients [12–14]. Heat sources in these applications are provided typically either by external heating or by solar radiation [15]. In addition, both infrared and color cameras have been used to perform visual inspections using vans or boats for top and side views of structures [16]. Infrared

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http://dx.doi.org/10.1016/j.autcon.2016.08.024
0926-5805/

images have been combined with GPS and image stitching tools to form geographic information system representations of a bridge deck [17]. Infrared thermography was further used in conjunction with acoustic approaches to monitor damage on a masonry walls under cyclic loading [18], or detect damage in concrete structural components [19].

Unmanned aerial vehicles (UAVs) have been extensively used for military applications while several civil applications are currently being developed for remote sensing [20,21]. For instance, color and infrared images acquired by a UAV were used to identify people in rescue operations [22]. In addition, multiple UAVs were used simultaneously to identify forest fires using color and IR images [23]. Near infrared (NIR) images obtained from a UAV have been used to identify crops from other objects like soil [24]. Similarly, IR images were used to determine the health of olive trees using an estimate of chlorophyll content and water distress [25]. Moreover, gas pipeline inspection was proposed using multispectral imaging and synthetic aperture radar, while recently permission was given to private contractors to survey pipelines with a UAV [26,27].

The use of UAVs in infrastructure assessment has been increasingly explored in the recent past. For instance, a helicopter UAV was used to power and read measurements from a wireless sensor [28]. A proof of concept for the use of a quadrotor has been investigated for the identification of power line joints using high resolution images and image processing [29]. A laser scanner and RGB-D sensor were added to a UAV to obtain point cloud information of outdoor buildings for inspections purposes [30]. In addition, an image based 3D point cloud reconstruction of a pedestrian bridge was completed by Lattanzi et al. [31] using a dense structure from motion method applied to UAV imagery. Despite challenges, this method could provide a global view of the structure as a tool to identify and locate damage.

For all applications involving remote sensing, especially systems that result into large datasets, it is important to eliminate redundant or insignificant data without removing important information. To achieve this objective, many image processing algorithms have been used to identify objects from images. For example, color was used with machine learning to classify images with rusted areas on bridges using a robotic platform [32]. In this context, the Hough transform has been used to identify lines in vineyards from UAV images to find unhealthy plants [33]. Furthermore, edge detection was used to identify cracks in building facades using UAV imagery [34]. Moreover, a method was developed using a region growing technique to identify delaminations from IR images of a manufactured concrete block with known defects [35].

In this article, a multirotor UAV was used to detect delaminations as well as to estimate their size in a mock up bridge deck based on IR and color imaging data. The locations of the delaminations were not known prior testing. The IR data was recorded onboard and was streamed back to the pilot during the flight which allowed the manual identification of defects in real time, justifying the capability of rapid inspection. The data collected was used post mortem by a novel post-processing algorithm which is based on the calculation of grayscale gradients and their directions in the IR images to detect and estimate the size of subsurface delaminations. The results obtained by using the UAV imagery were further validated by performing similar measurements with a similar multispectral payload attached to a moving cart to compensate for both payload and UAV motion uncertainties in the proposed approach.

2. Equipment

2.1. UAV and payload

A commercially available six-rotor UAV was used to conduct the aerial experiments. Fig. 1 shows each of the components involved in the payload and their exact positions on the UAV. Although the system is equipped with GPS, gyroscope, accelerometer, and pressure sensor for flight control and stabilization, the pilot flew the system manually for the measurements reported in this article, due to the close proximity of obstacles; however a completely autonomous flight is also possible. The UAV carried both a GoPro Hero 3+ silver edition color camera and a FLIR Tau 2 uncooled core IR camera to capture video imagery in real time from the bridge deck. The specific IR camera used is unable to make actual and accurate temperature measurements and the only output provided is a video of surface temperature gradients. At first, the color camera was placed on a gimbal to keep it level with the ground at all times, but due to weight limitations, the IR camera was fixed to the bottom of the UAV with a vibration dampening system instead of placing it on a gimbal. Difficulties in matching the color and IR data resulted in testing with both cameras fixed to the bottom of the UAV to determine a constant transformation between the cameras. The constant transformation was calculated using an over determined direct linear transformation or homography matrix [36]. At least four corresponding points in each image are required to solve for the transformation. Due to the way the cameras were installed on the UAV, the transformation was assumed to have scaling, rotation about the axis perpendicular to the image plane, and rotation within that plane. Therefore, only two corresponding points were necessary to calculate the similarity transformation. Up to corresponding 10 points were used in each set image to increase the accuracy of the transformation by using a least squares best fit. These corresponding points were manually selected in 10 sets of corresponding images. The rotation was negligible and the standard deviation associated with the translation was 4 pixels in the horizontal direction and 5 pixels in the vertical direction.

The color video was recorded using the memory card inside the camera and the IR video was saved onto a second memory device using an onboard digital video recorder (DVR). The color video had a 138° diagonal field of view, resolution of 1920×1080 pixels, and recorded at 30 frames per second. The IR camera had a 69° diagonal field of view, resolution of 324×256 pixels, and also recorded at 30 frames per second. The ground sample distance varied with the height of the cameras, which was not obtained during the test. The range of ground sample distance varied between 2.5 mm (at 2 m height) and 1.3 cm (at 10 m height) throughout the test. Both videos were streamed to the pilot using 2.4 GHz for the high definition color video and 5.8 GHz for the standard definition IR video. Fig. 2a shows an example of an IR image placed over the RGB image after the test. The UAV images were streamed back to the pilot allowing changes in the flight pattern based on areas of interest and observation in real time of potential delaminations.

The videos were recorded by the UAV to ensure no frames of the video were missing due to radio frequency interference caused by possible obstacles between the system and the ground station. Both videos were projected real-time onto screens so the pilot could see what the UAV was capturing. A diagram of the data flow and an image of the ground station and UAV are shown in Fig. 3. The receiving antennas were placed outside of the van for the experiments to limit the problem of shielding which would cause breaks and jumps in the video streams.

Due to the number of video components on the system and the need to control the video systems separately, a second battery was added to the system to power the video components. The total takeoff weight of the system during the flights was 2.6 kg which is close to the maximum recommended takeoff weight for this UAV. Despite this added weight, the system achieved flight times of up to 7.5 min.

2.2. Validation equipment

A ground system including again both infrared and color cameras was used to validate the results obtained by the UAV. A GoPro and a FLIR a325sc were attached to a rolling cart and moved along the deck to identify the delaminations. Fig. 4 below shows the setup of the FLIR, GoPro, power, and recording system contained on a cart. Since a generator was used to supply power, the whole system could be moved easily without connection or range problems due to power cords. This allowed for smoother movements which made the data easier to process.