Applications of Computer Vision in Structural Health Monitoring

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Abstract

Recent advances in computer vision to explore new sensors and sensing platforms have shed light on the potential for autonomous structural health monitoring in civil engineering structures. The use of low-cost, high performance cameras in conjunction with aerial or embedded sensing platforms, can overcome spatial and temporal limitations typically associated with visual sensing. Moreover, the availability of well-established algorithms in computer vision enable quite efficient and rapid analysis of the visual data collected. However, beyond simply processing these images, aiming to replicate the actions and abilities of human vision enables autonomous decision-making. Several computer vision techniques, such as image processing, object detection, or multi-view geometry, are increasingly being implemented for a variety of applications in civil engineering. This paper considers the novel use of computer vision methods to address two promising SHM applications in civil engineering: (1) visual inspection and (2) vehicle classification. The main contribution of the investigation is to provide a new framework for automated visual inspection using a large volume of images. The use of high-level image processing and analysis, when integrated with prior knowledge of general damage features, enables reliable visual inspection. The second investigation demonstrates the novel repurposing of object detection techniques that originate from computer vision methods to address vehicle classification. It is expected that repurposing of such algorithms has potential to impact civil engineering needs, among those in other fields, at a variety of levels.

1. Introduction

Visual sensing provides crucial and abundant information regarding the condition of a structure. Because visual changes provide obvious warning signs that the structural condition is deteriorating, visual inspection is still the primary method used for structural assessment. For bridges, most decisions relating to bridge maintenance are based on visual inspections. However, human oriented visual sensing has certain limitations, especially in large-scale structures. Limitations revolve around consistency, accessibility, safety and efficiency. Also, highly qualitative and subjective evaluation are inevitable in human vision (Phares, 2001).

To overcome these limitations, many researchers have focused on the development of algorithms and techniques for vision based autonomous visual inspection to facilitate structural health monitoring (SHM) (Jahanshahi, et al. 2009; Abdel-Qader, et al. 2003; Zhu, et al. 2011; Sinha, et al. 2006). These methods have been found to be reliable and accurate for various inspection tasks. Unfortunately, they are rarely implemented in real applications to date, especially in civil engineering. Civil structures are relatively large and exist in harsh environments, introducing challenges in accessing various regions for viewing the structure, and thus in collecting images. Moreover, the analysis of large quantities of images are computationally expensive using conventional image processing techniques. However, recent developments in machine vision technologies are enabling more efficient and cost effective visual inspection.

Recent advances in the various sensors and sensing systems achieve remarkable visual sensing capabilities, enhancing granularity in both time and space using automated methods. As imaging sensors have become smaller, cheaper and more powerful, quite a large number of sensors can be spatially distributed and are thus readily available for fulfilling the various essential tasks. Some sensors, such as wireless sensor nodes, are intended to be embedded in structures, and have appropriate embedded computational processing capabilities (Lynch, et al. 2006). Moreover, recently commercialized drones (unmanned aerial vehicles) have expanded sensor mobility from ground to sky (Ortiz, 2014; Angel aerial survey, 2014; US Aerial Video, 2014), and a head-mounted optical display such as Google Glass™ or action cameras has received significant attention for its ability to record and learn human actions (Google, 2015; GoPro, 2015). The new opportunities facilitated through availability of these powerful sensors and sensing systems are beginning to compete with human vision inspection in terms of cost and performance.

Once visual data is collected, it must be organized, processed and analyzed to extract useful information. The field of computer vision is devoted to such problems of interpreting the world through the analysis of visual images. Beyond simply processing images, recent advances focus on replicating the abilities of human vision such as search, retrieval or learning. Automation of these processes will enable quite efficient and rapid analysis. Moreover, integrating these processes across multiple images, while incorporating their spatial and temporal information, will greatly expand their usability in higher dimensions and provide deeper insight. This capability will provide the capacity for automated analysis to support decision-making beyond that of human interpretation (Szeliski, 2010; Hartley, et al. 2003).

The opportunities associated with automated processing and advanced sensing systems have accelerated the work to develop autonomous visual methods for SHM. Futuristic visual inspection might be imagined as follows. An unmanned aerial vehicle (UAV) equipped with a high resolution camera or vision sensors, such as infrared or thermal camera, arrives at candidate structures or construction sites. Following a flying path designed *a priori*, using GPS, the UAV automatically flies the designated route to collect and record images. Using previous inspection records, this flying path is periodically updated to target more vulnerable components. For example, it may be important to take more images in areas of interest that were detected and identified in previous flights. The UAV transmits the collected images to a base station. At the base station, processing takes place across the large volume of images. The image processing at this point be focused on many purposes. Typical examples include oversight of the construction process and equipment, inspection of damage on the structure, or post-hazard assessments to improve situational awareness. The system automatically generates an inspection report to inform high-level decisions by the owner or engineer. Furthermore, by preserving such reports and documenting the decisions and actions taken over the lifecycle of the structure, such a system will contain a complete record of the condition of the structure and decisions made, and would provide evidence to facilitate better decision-making for other structures. Thus, the inspection process would evolve over time, becoming smarter and much more efficient.

Herein we first introduce a new approach for autonomous visual inspection, increasing the feasibility of this future vision for condition assessment and lifecycle management. The use of high-level computer vision methods, when integrated with prior knowledge of likely vulnerabilities and general damage features, enables reliable visual inspection. Second, we explore the translation of the technologies used in the first application to tackle an entirely different problem, which is vehicle classification on a mobile bridge. The problem here is not an application of visual inspection. However, it is shown that repurposing of the same object detection algorithms has potential to alleviate challenges in other civil engineering fields, among those in other fields. After a brief literature review of image based autonomous visual inspection in civil engineering, we focus on these two applications demonstrating successful application of computer vision methods to solve two very different problems.

2. Literature Review

Vision based autonomous inspection is not a new concept and has been broadly developed and used for civil, mechanical or aerospace structures. In the past many researchers have proposed vision based visual inspection techniques by automatically performing the specific tasks set forth in the manual (Indiana Department of Transportation, 2013). However, for civil engineering, the major tasks encompassed by visual inspection can be grouped according to the two most common materials used, concrete and steel, which exhibit entirely different characteristics when it comes to damage.

Defects in concrete, similar to asphalt pavement, typically manifest as cracks or delaminations. First, cracking is a major mode of damage in concrete, and inevitably occurs at initiation or during operation. However, a crack can be the result of one or a combination of factors such as drying shrinkage, thermal contraction, restraint shortening, subgrade settlement, and applied load (Portland Cement, 2001). Thus, the occurrence of a crack in concrete is not necessarily a cause for concern, but should be left to the judgment of the inspector. The appearance of a crack has a mostly clear low intensity than background and its pattern is a straight or curved line with a relatively uniform width. Thus, intensity based edge detection and segmentation approaches are widely used (Abdel-Qader, et al. 2003; Jahanshahi, et al. 2009; Yamaguchi, et al. 2010). However, the challenges include: (1) similar appearance as that of other edges present, (2) connection of disjointed cracks detected, (3) scale estimation, and (4) image corruption due to environmental conditions, such as shadows or dirt. Various techniques have been proposed to overcome these challenges such as statistically learning to identify crack appearance for classification, quantification shadow-removal and connecting crack fragment (Zhang, et al. 2014; Jahanshahi, et al. 2013; Zou, et al. 2012; Subirats, et al. 2006). Second, delamination, such as flaking or spalling, is another likely damage scenario that could be investigated with visual methods. Abrupt delamination damage like spalling or potholes, can pose damage to users as well as accelerating another mode of damage, such as corrosion on steel rebar. Texture analysis and shape extraction techniques are used to extract damage areas in 2D (German, 2012) and multi-view geometry is applied to obtain geometry information in 3D (Koch, 2011; Torok, 2013).

Steel is a uniform solid material, and yet it is susceptible to environmental and operational conditions. Corrosion is a common source of damage in steel, causing material degradation. Corrosion appears as rust on uncoated, visible surfaces, and color based corrosion detection and texture based corrosion have been widely studied (Lee, et al. 2006; Chen, et al. 2009, 2012; Jahanshahi, et al. 2012; Bonnin-Pascual, 2014). Second, steel cracks, mainly fatigue cracks, occur at areas of stress concentration and frequently originate at a flaw associated with a weld or material inconsistency. Detection of cracks in steel can be more difficult than in concrete because the cracks have thin, shiny edges and may be invisible depending on lighting conditions and viewpoints. Similar to cracks in concrete, edge-detection and segmentation techniques are used for detection of visibly clear cracks, but they would require higher resolution images or large crack sizes for ready detection (Neogi, 2014).

3. Vision based Automated Visual Inspection

Visual inspection is the customary approach to identify and evaluate faults in bridges. Current procedures required for human inspection processes demand long inspection times to examine bridges, especially when they are large or difficult to be accessed. Also, the reliance on an inspector's subjective or empirical knowledge has the potential to induce false evaluation or inconsistencies (Phares, et al. 2001). To address such difficulties, a vision based inspection technique is proposed. Automatic capture, processing and analysis of a large volume of collected images is enabled, with minimal restrictions on the images captured. Images to be used can be captured without restricting or specifying the angles and positions of the cameras, and there is no need for prior camera calibration. In this study, automated crack detection is demonstrated using images collected from an unmanned aerial vehicle (UAV), for instance, using a drone.

Consider the question: Given a large volume of images, perhaps from an aerial vehicle, would it be feasible to detect damage in a realistic structure using currently available vision based damage detection techniques? To answer this question, multiple photographs were acquired from a rusty, steel beam with a real fatigue crack initiating from one of the bolt holes. Data analysis was performed using image processing techniques available in the literature (Jahanshahi, et al. 2009). In this examination, two major issues are identified, which need to be addressed to enable automated, effective and efficient vision based inspection. First, many false-positive alarms and misdetections may result when simply searching for cracks over the entire area of an image. Several crack-like features are present in most images such as structure boundaries, wires, or corrosion edges. These may cause either incorrect detection or a failure to detect real cracks due to its narrow width. However, human inspectors can typically detect the actual crack. An inspector's prior knowledge about a crack's typical appearance and characteristics is helpful in determining if a crack is present. In this case, the relevant information is that new cracks on a steel structure have thin, shiny edges, and often initiate and propagate from bolt holes (Indiana Department of Transportation, 2013). These features will draw the inspector's attention to the bolts and nearby areas, facilitating crack detection in these more vulnerable areas. A second issue observed is that the crack may or may not be visible depending on the viewpoint from which the image is acquired. This concludes that same scene may appear to be very different from multiple viewpoints, and many images may be needed to detect the crack without knowing how it originated or propagated. Much of the previous research, of course, has unconsciously considered these two issues. Images are collected under controlled circumstances, with camera positions or angles chosen based on the appearance and location of cracks. However, in reality, the capture of sufficiently good images taken under the "best" conditions cannot be predicted or expected because the crack location, crack direction and lighting direction cannot be known in advance. Furthermore, it is hard to precisely and continuously control camera positions and angles when it is installed in the UAV.

Rather than searching for cracks throughout entire images, the specific objects that have areas susceptible to cracks (bolts in this study) are first detected in each image. This initial step greatly increases the detectability of cracks by narrowing down searching areas and damage scales in the acquired images. Next, object detection and grouping techniques available for computer vision can be implemented to extract, match and group the same objects from many angles across the entire large set of images.

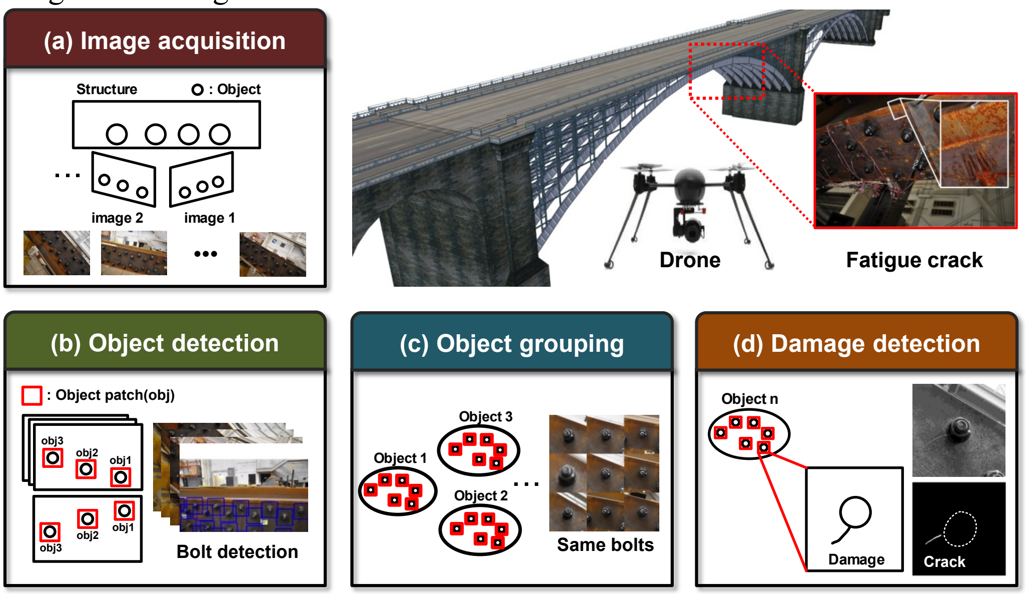

Figure 2. Steps in the proposed automated visual inspection technique

A diagram of the proposed technique is provided in Fig. 2. First, in Fig. 2 (a) images of the structure are collected from many angles using the chosen image acquisition equipment (e.g., aerial cameras or inspection robots). Second, in Fig. 2 (b) the targeted structural components (called objects), which are susceptible to crack damage, are detected and extracted from each of the images. The object patch indicates one such object and its nearby area where the presence of a crack damage is more likely. Third, in Fig. 2 (c), common object patches (corresponding to the same object) across the collection of images are matched and grouped. Finally, in Fig. 2 (d), the proposed crack detection technique diagnoses that a crack exists in the structural components.

A rusty, full-scale I-beam having 68 bolts, as shown in Fig. 3, is used to validate the proposed techniques. Rather than cycling the beam to produce fatigue cracks on the beam, two artificial scratches are made with an awl at locations A and B. Fig 2 shows sample images and outcomes in each steps. Due to space limitations, all of the details regarding intermediate parametric and numeric outcomes (Yeum and Dyke, 2015). All objects, identified as the damage sensitive regions, are properly detected and grouped, and the two induced artificial cracks are successfully detected using this large collection of images.

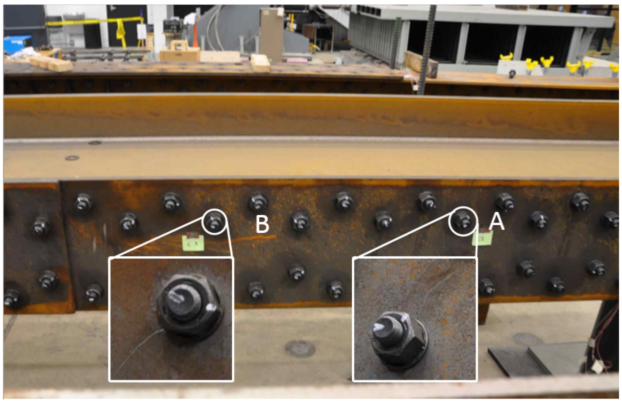

Figure 3. Specimen: a rusty, steel beam with 68 nearl identical bolts

In this application, to demonstrate one typical automated visual inspection task, we select to occurrence of cracks occurring near bolts on a steel structure for demonstration. However, users can extend the proposed visual inspection framework to conduct other types of visual inspection. For example, suppose that corrosion or crack damage in gusset plates is the damage case of interest. The gusset plates would become the “objects” and the technique proposed would be applied to extract images of individual gusset plate taken from various angles. Users would be able to analyze images of all gusset plates in a bridge by applying a suitable crack detection criterion, as demonstrated in this application.

4. Vehicle Classification on a Mobile Bridge

A mobile bridge, shown in Fig. 4, is an essential structure to facilitate short-term mobility when faced with natural or man-made obstacles (e.g., General Dynamics, 2015). When a mobile bridge is deployed, it is necessary to rapidly confirm that it is safe before use or entry. Typically, such an evaluation is based on the usage history, and thus a simple method for accurately determining vehicle types and number of crossings is needed. There are several factors that must be considered here. First, the usage pattern is irregular. The bridge is intensively used when deployed, but the rest of time it may be stored. Second, its behavior is often non-linear with a need for carrying high static loads and experiencing sudden impacts, and vehicle loads often exceed the weight of the bridge itself. Lastly, it is used under a variety of boundary and environmental conditions. Weather conditions and surface conditions will both influence the boundary conditions. A passive sensor has been used in the past, known as a Remaining Service Life Indicator. It uses four metallic “filaments” that are designed to crack after a specific number of vehicle crossings (Department of the Army, 2006). However, a more suitable approach would help to collect more detailed information regarding usage.

For bridge applications, there are a couple of commercialized systems for estimating classes of vehicles or their axle weights, called bridge weigh-in-motion (B-WIM) (Cestel, 2015). Unlike conventional WIM techniques, sensors are installed beneath the bridge to avoid modifications to the bridge deck or addition of sensors on the bridge surface. However, there may be concerns with ensuring long term sensor adhesion for strain sensors.

The technique proposed here will monitor bridge usage patterns using embedded low-power wireless accelerometers. It is intended to estimate the class of each vehicle traversing the bridge using an acceleration measurement. We make the assumption that one vehicle is crossing the bridge at a time, which is quite reasonable for typical mobile/temporary bridges. In this technique, an object detection algorithm from computer vision is also implemented to extract features and train classifiers. Once classifiers are constructed for each class of vehicle, users would not need to perform further manual calibration on site for classifying vehicles.

The basic concept behind the proposed technique is that each vehicle crossing the bridge produces unique dynamic patterns, which makes it distinguishable from other vehicles. Even under reasonable variations in the vehicle speed or mass, or if data is collected at different locations on the bridge, it can be assumed that those patterns are preserved. This concept is analogous to object recognition. Even if we acquire photos of objects with different angles or lighting conditions, a human can intuitively notice the "difference" of those objects by automatically integrating several features and overall patterns. Modern object detection and classification algorithms have tried to mimic the human's "difference" detection capability and have made tremendous gains (Viola, et al. 2001). In this sense, the proposed technique applies those powerful algorithms to tackle the vehicle classification problem. In this study, an established object detection algorithm, proposed by Viola and Jones, is applied for features selection and classification (Viola, et al. 2001; Bishop, 2006). The feature selection process used here is completely automated and does not rely on prior information about the objects. When the acceleration signals are transformed into a form of images and are labeled as vehicles, this method can produce robust and reliable classification results.

However, in the mobile bridge application, patterns produced from each vehicle may not be consistent across under different installation conditions of the bridge. There is the challenge that the dynamic characteristics of the bridge are different based on the installation conditions. To address this problem, the proposed technique first identifies the closest training data set by driving a known (reference) vehicle across the bridge just after bridge installation. The training data set is used to identify the appropriate data patterns to use for vehicle classification given the bridge setup. The reference vehicle may be, for example, a truck responsible for transporting the bridge, but any vehicle might be used for this purpose. Once the dynamic patterns associated with the bridge setup are identified, the same algorithm is used for classifying and count the vehicles.

The overall procedure is divided into two steps: training and testing. In the training process, different bridge setups are used to classify the vehicles. Collection of training data sets under many different bridge conditions is recommended to cope with real bridge implementation. Each training data set has classifiers for all vehicles as well as a classifier for the corresponding training data set. Once the bridge is installed, the reference vehicle would drive across the bridge to identify the closest training data set. Then, classifiers obtained in the training data set are used for classifying the vehicle. Haar features based boosted classifiers are used for this technique, which was proposed originally by Viola and Jones (2001). First, the raw acceleration signals are cropped to remove unnecessary portions (i.e. before entrance, and after exit). A moving root-mean-square with a proper threshold is used for accurate estimation of the times for the vehicle entrance and exit. Second, the signals are converted into a spectrogram for analysis in the time and frequency domains, and forming a two dimensional image containing this view of the acceleration response of the bridge. A wavelet transform may also be used for this process. With proper tuning of the spectrogram parameters, including the number of time increments and the number of spectral lines in the FFT, an appropriate image is generated. Similar to the case of object detection, the use of high resolution images of this spectrogram may help with classification, but does not greatly impact detection rates. Thus, users will need to tune these parameters depending on detection rates as well as computational capabilities. Third, Haar-like wavelet feature windows are applied to the spectrogram images for feature extraction. The use of integral images provides an effective method for calculating the relevant features. Finally, based on these features, a robust classifier is designed to determine whether the features indicates a specific vehicle or not. A binary classifier is used, and each vehicle will have its own classifier corresponding a training data set.

Figure 4. A typical mobile bridge (General Dynamics, 2015)

In this study, a boosting algorithm is implemented to produce robust classifiers. Boosting is a way of combining many weak classifiers to produce a strong classifier. By updating different weights of weak classifiers adaptively depending on misclassification errors, the optimum strong classifier, which minimizes misclassification errors, can be obtained. Several boosting algorithms have been introduced in the literature, but in this study, the gentle boost algorithm, proposed by Friedman, is used because it is known to be simple to implement, numerically robust and experimentally proven for objection detection (Torralba, et al. 2004; Friedman, et al. 2001). The details of the gentle boost algorithm can be found in (Friedman, et al. 2001).

To validate the proposed technique, an experiment is conducted using a typical mobile bridge in Fig. 4. This preliminary experiment is intended to illustrate the general concept of the technique. A total of 12 wired accelerometers, 6 on each side, are installed to collect typical data on vertical vibrations. Two different vehicles (sport utility vehicles) each with two different speeds (unknown) drive across the bridge four times each. A total of 192 data samples are obtained, and each is labeled as either vehicle 1 (V1) or vehicle 2 (V2). In this experiment, no variation of the bridge conditions were possible, such as boundaries or bridge length. Thus, there is only one training data set in this case. Among the 192 data samples, 20 data are randomly selected for validation of the method and the remainder are used for training.

Using this experimental data, we classify the 20 random test cases of the crossing of the two vehicles using the proposed technique. Final classification results are shown in Fig. 5. The blue circle and red x are the true and estimated vehicle classes, respectively. Nineteen samples are correctly classified among the twenty data records. The procedure is repeated several times with a different set of training and evaluation data, and in each case at least nineteen correct classifications were obtained. Further investigation of the method will take place, with more vehicles and varying bridge conditions. The results of this preliminary experiment indicate that: (1) unique patterns exist for each vehicle's acceleration signal, and (2) correct extraction of those patterns facilitates vehicle classification with the proposed procedure.

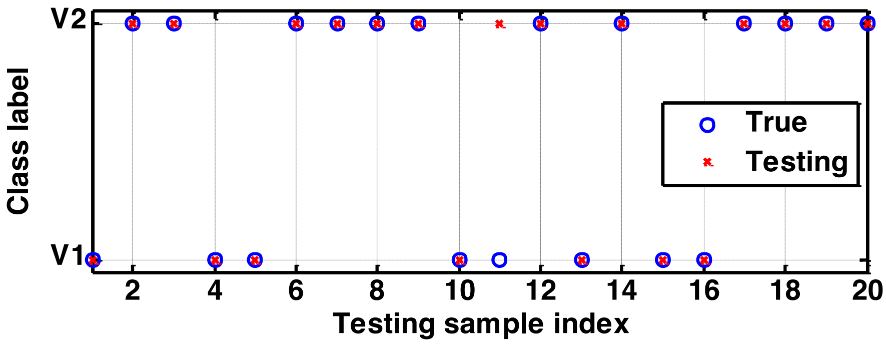

Figure 5. A result of two vehicle classification results

5. Summary

This study considers the implementation of computer vision technology to solve two different problems in SHM supporting decision making: visual inspection and vehicle classification. Various techniques in computer vision, from image processing to machine learning, are used for each of the tasks producing successful results. It is anticipated that such repurposing of technology has the potential to address several other applications within SHM.

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