A COMPUTATIONAL FRAMEWORK FOR NEXT-GENERATION BRIDGE IMAGING AND INSPECTION

David Lattanzi and Greg Miller
Dept. of Civ. and Env. Engr., University of Washington, Box 352700, Seattle, WA, U.S.A.

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Abstract: A modern framework for bridge monitoring is proposed. It is intended to, in effect, bring bridges virtually into engineers' offices, enabling computer-assisted inspection using visual/spatial navigation and interaction, augmented with computer vision recognition and analysis techniques developed for flaw and damage detection. The technical challenges to be addressed include developing a robotic front-end image capture approach for optimum compatibility with the bridge inspection process, building scalable back-end visualization algorithms, implementing a computer vision system capable of robust field inspection, and leveraging the contextualized image data to improve decision making tools for bridge maintenance.

1 INTRODUCTION

Bridges represent a critical component of infrastructure systems, and therefore condition monitoring via periodic inspection has long been a key part of bridge operations and maintenance practice. Current bridge inspection technology typically requires an inspection team and support equipment to travel to a given bridge to make a series of qualitative observations. Thus, there are a number of personnel, equipment, and travel costs inherent in this approach that scale linearly with the number of bridges needing inspection, the frequency of inspection, the distance between bridges, and the life of the bridges. There are more than 576,000 bridges in the US alone, most all of which must be inspected every two years, and so hundreds of millions of dollars per year are spent on inspections. There are also substantial indirect costs associated with required lane closures and related traffic disruptions. Making bridge inspection less costly, less obtrusive, more quantitative, and more effective in regards to the type and quality of data collected thus can lead to significant economic savings and safety improvements. This includes reductions in both the direct and indirect costs of the inspections themselves, the avoidance of unnecessary repairs, the timely implementation of needed repairs, and the opportunity for improved engineering that comes from improved understanding of field performance of designs over time.

During a structural inspection, inspectors capture local measurements and close-up images of critical bridge components and damage. However, these photographs and measurements are notoriously difficult to comprehend by anyone other than the inspection team themselves, as they are captured and organized in such a way that they are decontextualized. The images are also presented in a qualitative manner, with no standard methods in place to objectively analyze them. An inspection report which, includes the decontextualized data, is passed to an engineer who is responsible for assessing deterioration to the structure, considering the temporal context of the inspection information. The engineer then passes an assessment to managers charged with high-level policy decisions concerning system-wide resource allocations. In general, the movement of data up through this decision-making hierarchy results in huge losses of potentially useful and critical information, and this is equally true in regards to the the transfer of data across time. Contrasting the effort and expense required to complete a typical bridge inspection with the resulting outcome of passing up the chain a set of coarse-grained, essentially qualitative assessments, it is clear that the cost-to-information ratio is unfavorably high.

2 RESEARCH PROGRAM

An alternative, complementary inspection approach is

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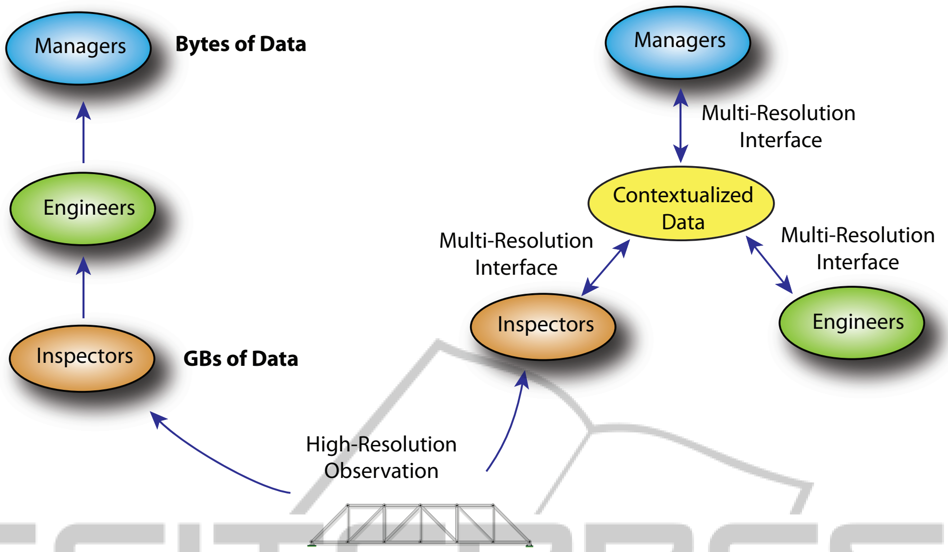


Figure 1: Current (left) and proposed (right) methods of information transfer.

to is to use modern imaging methods that in principle can deliver image data from anywhere (and thus everywhere) on a structure. Computer vision and visualization methods can supplement the traditional qualitative visual inspection process, increase the effectiveness of embedded sensor systems, and, coupled with robotic inspection platforms, enable an entirely new level of consistency, efficiency, and safety via full automation. Visualization systems based on digital imaging techniques can allow engineers and owners to perform time-history analyses that span the decades of a bridge's in-service period. The key in all these contexts is to have a framework for providing easily catalogued and understood data at both the local and global level.

The fundamental concept to address this high-cost/low-value information problem can most easily be understood via reference to Figure 1. This figure contrasts the current linear/hierarchical, lossy information flow with the proposed alternative based on providing registered and catalogued centralized data throughout the decision-making hierarchy. In addition to providing much greater access to information at the decision-maker level, this approach also greatly enhances the possibilities for inventory-wide analysis and data mining. Of course, for such an approach to be useful it must be possible to be able to interact with the data at varying resolution levels and in different ways at different times, ranging from viewing close-up detail images to performing inventory-wide cost estimates for repair or replacement. The inherently spatial nature of inspection and assessment data also requires an organizational strategy that intuitively represents localized information. Interactive 3D visualization environments, which also serve as fully 3D databases, can consider both the spatial and temporal context of infrastructure assessments. Once combined with rich user interfaces, a new model for data driven infrastructure maintenance and management begins to take shape.

It is useful to consider a future scenario in which the envisioned technologies are fully realized. In this scenario an engineer receives notice that new inspection data have been obtained from a particular bridge (in the fully automated case, via a periodic robotic traversal requiring no traffic disturbance, crew travel/safety risk, or equipment rental). The engineer brings up the data in the context of an interactive geometric model of the bridge and queries the system to show all new indications of damage or deterioration since the previous inspection. Each indicated location can then be zoomed in on and examined with in-context, high-resolution images simulating the experience of viewing the structure in the field, but with optional image enhancement highlighting damage. A second query could then request an update of all previously existing indications of damage or deterioration, followed by zoomed-in animations of the evolution of the damage over time. A third query could request that a particular area of damage be compared against a national database to compare rates of growth relative to similar flaws in similar classes of structures, which could further be used to extrapolate growth rates. A fourth query could ask for correlation between damage growth between inspections and embedded sensor data indicating loading and other environmental history during the period in question. In the case of ambiguous or unclear visual data, additional

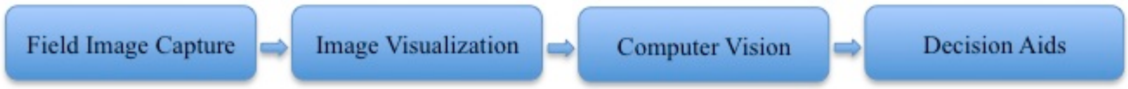


Figure 2: The proposed bridge inspection framework pipeline.

inspection could be requested using alternative sensing modalities (e.g., ultrasound, infrared, etc.), and so on.

3 METHODOLOGY

Figure 2 shows the key components of the capture/visualization pipeline that must be developed in order to realize the proposed inspection framework. The following subsections describe in further detail the approaches to be used in addressing the technical challenges associated with each component of this pipeline, and the anticipated outcomes.

3.1 Image Capture Methods

Upgrades to traditional methods of in-the-field image capture (inspection teams with cameras) are being explored alongside the use of automated, robotics-based capture. The challenge in the traditional case is to develop a user input data-logging technique paired with a combination of computer vision techniques to extract location and orientation data from the captured images so they can be properly integrated into an overall geometric context. For the complex geometries common in bridges, this is a challenging task, especially when combined with the variability in human-driven capture.

Similar geometric challenges arise in the case of robotics-based image capture, but there are more opportunities for precise control and repeatability on the capture front-end. By design, robotic devices can track their position, camera orientations, and viewing angles with high precision, allowing for precise data logging and repeatable imaging, effectively skirting the key difficulty of the inspector focused approach. Furthermore, such mobile systems can quickly and unobtrusively access structural elements that are difficult or impossible for human inspectors to view without significant disruption to traffic and risk to the safety of the inspectors. Combined with the fundamental advantages of automation, the robotics-based approach is particularly compelling, but this raises the question as to why it is not being used currently.

In looking at prior robotic bridge inspection work, it can be seen that over the last decade researchers have developed several chassis designed for bridge inspection (Choset, 2000; Huston et al., 2003). A common focus of this work has been on developing mechanisms for traversing arbitrary bridge geometries using approaches such as magnets, suction, and other climbing technologies (Mazumdar and Asada, 2009). These systems have been developed in an attempt to create a “one size fits all” robot that can inspect almost any bridge type currently in service. In all but one case, these have been proof-of-concept robotics projects which have at no point actually carried a sensor or vision package in actual field testing.

Our approach is to use a simple and inexpensive mobile platform, with an emphasis on creating modular robotic systems designed for use on specific structural systems. Specializing to specific structure types and applications yields significant time and cost savings over general mobile platforms designed to inspect any and all structure types. Even in more general contexts the mechatronic systems required for a specific application can be substantially simpler and cheaper than a machine designed for a more general set of criteria. This specificity allows for smaller inspection devices that can pass through smaller spaces, inspect portions of structures that would be inaccessible to larger multi-purpose inspection equipment, and more easily navigate the details of bridge structures. Developing an inspection system around a series of smaller, specific mobile machines could also eventually lead to a modular platform where various mechatronic, sensing, and data processing packages would be interchangeable based on the demands of a given bridge inspection environment. Lastly, the use of simpler robotic systems has a significant and positive impact on manufacturing costs, and may mean the difference between the ubiquitous use of inspection robots and their dismissal as impractical.

The robotic test platform enables the investigation of both visual and other modes of inspection data not currently available through static sensor networks. The prototype robot, designed for use in laboratory testing situations (Figure 3), contains a sensor array that includes the digital imaging system, thermal sensors, tilt sensors, and accelerometers. All of these sensors are lightweight, low power, small, and easily incorporated into the mobile robotics platform. The combination of sensing paradigms affords an opportunity to explore the association between general sensing and imaging data, and is lending significant insight into our understanding of how visually observable damage correlates to local and global structural performance characteristics. For instance, an onboard sensor package yields valuable environmental information such as the ambient temperature at the time of inspection or the concentration of chlorides and other chemical detriments.

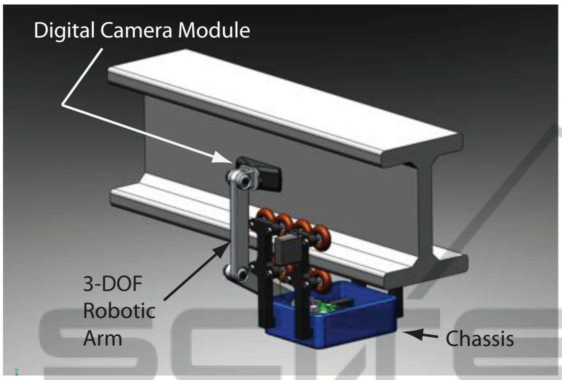


Figure 3: Simple mobile platform concept for lab testing.

3.2 Image Visualization

The generation of massive amounts of image data is not in itself a helpful exercise without some mechanism for structuring and presenting the images in useable forms. The basic idea of presenting captured images in a natural 3D context has long been used in medical, dental, and related health-care fields, generally leveraging the benefits of 3D imaging technologies. Similar to what one would want for bridge inspection, the goal has been to leverage trained human observational skills with computer vision, image processing, and visualization. This leads naturally to presenting data in 3D contexts in such a way as to reproduce an observational experience similar to direct physical observation.

The basic task of associating captured images with surface representations of 3D objects involves registration (assigning proper geometric location), multiple image merging/stitching, and texture mapping, all of which are relatively mature technologies (see, e.g. (Cox and Jesmanowicz, 1999) for registration and (Chen and Klette, 1999) for stitching/merging). Image registration and merging are aided by the developed data-logging methods in the human-led approach, and by the geometric accuracy and record-keeping inherent in the robotic approach.

A naive approach to making a visualization system for the inspection applications would be to simply use standard texture mapping to assign appropriate images to each surface polygon of an underlying 3D bridge representation model. However, consider for illustrative purposes a 24-foot-long W24$\times$68 to be covered with 1200$\times$1200 pixel tiles (1.4 megapixel images) corresponding to 3-inch square patches. A simplified calculation based on computing the overall member surface area, estimating the number of patches required by dividing by 9 square inches/patch, converting the result to a number of pixels, and assuming 24-bit color with no compression leads to an estimate of about 12GB of storage for direct tiling of a single, simple member. Although this is a small fraction of the data that a larger-scale system like Google Earth must manage, it still easily exceeds the memory capacity of typical video cards, and so this kind of direct approach to interactive visualization is not scalable for bridge-scale modeling. (There are numerous compression and selective resolution-reduction strategies that can be used to reduce the overall storage demands, but at visualization time, the rendering engine must have access to actual texture data at a resolution suitable for the current viewing parameters).

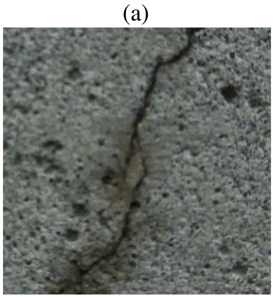
To address this kind of data-overload problem, programs such as Google Earth uses a combination of technologies to provide interactive multi-resolution navigation through extremely large image sets. The fundamental building blocks consist of multi-resolution pixel map textures (mipmaps), and clever clipping algorithms (Tanner et al., 1998) allowing for the interactive handling of huge data sets on modest client hardware. Google uses its own proprietary implementations, but there are analogous strategies available to build similar capabilities for the case of bridges. The challenge in the context of bridges, though, is that while the problem is more modest in terms of size, it is much more difficult in terms of the target geometry: the earth is ultimately a sphere, while bridges have much more involved topology and geometry.

3.3 Computer Vision

From a computer vision standpoint, the challenge is in creating vision algorithms that are robust to the highly varied imaging scenarios prevalent in field inspection. Most computer vision systems developed for infrastructure damage detection are based on image capture scenarios which are highly controlled against variances such as changes in lighting. Such controlled systems are afforded the luxury of tuned filters for providing accurate results. However, in-service structures exhibit a wide range of variances in lighting, camera position, and structural surface appearance, among many others (Figure 4). This issue is illustrated in Figure 5, which compares the Kappa score accuracy of two basic computer vision systems.

The two systems were developed and tested on images of cracking in structural concrete. One system uses an edge detection segmentation technique commonly cited in damage detection literature(Abdel-Qader et al., 2003; Hutchinson and Chen, 2006), a method requiring significant amounts of filter tuning. The other system uses a clustering technique which requires almost no filter tuning. Both systems perform well if the image set is well-controlled with little image variance. However, once the image set becomes more varied, the performance of both models decreases. In the case of the edge based method, the drop in performance is much larger. Essentially, the inspection environment precludes the use of most traditional vision techniques and creates a demand for robust vision systems that require a minimum of tuning to function accurately considering a wide range of field conditions.

(a)



(b)

Figure 4: Example of variance between field images.

3.4 Decision Making Aids

A powerful product of the contextualized visualization and associated vision system is the provision of important data currently unavailable to engineers(Zaurin and Catbas, 2010). By registering observational data spatially and chronologically, it becomes possible to quantitatively associate processed image data with other inspection data such as damage measurements and condition ratings. In the context of pattern recognition methods, catalogued and parameterized image data significantly increases the robustness of any descriptor vector. The improved and

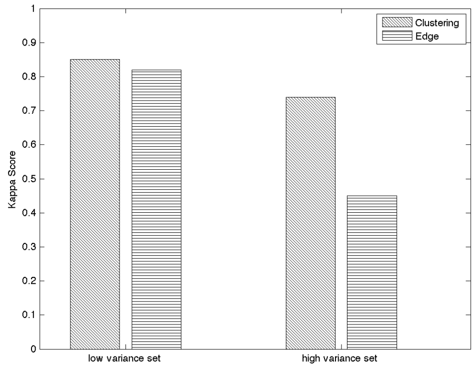


Figure 5: Kappa score comparison for models built using low and high variance image sets.

expanded data set has the potential ability to predict structural life spans based on developed learning algorithms, either by extrapolating damage growth rates from previously catalogued images of the damage, or by statistical comparison with other known instances in other structural models via pattern matching methods. Determining cost and risk indicators based on the sum of all inspection data is, while almost impossible for a human, a task well suited to computational intelligence techniques. Such quantitative indicators of the severity of structural damage could significantly alter the structural rehabilitation and replacement decision process currently in place.

4 STATUS OF RESEARCH

Researchers at the University of Washington have developed a visualization environment for contextualized viewing of inspection images and data which utilizes a hierarchical database system to manage the multitude of necessary images. Images are parametrically mapped, calibrated, and stitched using a localized feature detection approach. SURF feature detection and description(Bay et al., 2006), implemented via openCV (Bradski, 2000), has proven to provide a good blend of speed and accuracy for matching. The matching and stitching algorithm is being tested for robustness with inspection images.

The computer vision system (Section 3.3) has been tested and validated. Using a variant of a k-means clustering algorithm which takes into account the inherent appearance of structural damage, a highly accurate and robust recognition system has been implemented within the framework. Preliminary results show a marked improvement in robustness over current practice.

Leveraging the accuracy, spatial context, and convenience of the extracted image data, current research is directed at fusing image data with other inspection information. As a pilot project, synchronized image and sensor data from a series of seismic bridge pier tests are being combined. Such a fusion could provide an effective post-earthquake assessment tool.

5 CONCLUSIONS

A modern framework for bridge inspection, one that leverages computer vision and visualization techniques, has been described in general terms. This framework fundamentally changes the way that inspectors and engineers interact with inspection data, providing a contextualized viewing environment that allows for wide bandwidth transmission of inspection data well beyond what current strategies provide. Furthermore, this contextualized system enables the use of automated damage detection and analysis techniques that are unavailable under current practice protocols.

Two image capture methods are currently being explored: an inspector-driven approach and a simple robotic approach. Of the two methods, the robotic approach has the significant advantage of minimizing traffic disruptions due to inspection shutdowns. Software challenges include the development of scalable texture map storage and display algorithms as well as robust computer vision methods which can accurately and consistently segment and parameterize highly variable field images.

Once the system is implemented, the intent is to explore how contextualized (both in space and time) image data can expand pattern recognition and data mining techniques for long-term bridge service life prognostication and rehabilitation cost predictions.

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