

## **An Approach to Automated Detection of Failure in Temporary Structures using Image Processing**

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### **Abstract**

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This paper suggests video processing methods for monitoring temporary structures to detect possible structural failures. The causes of failures are mainly related to human error, but the imposed loads of structural failures can also be caused by complicated events such as accumulated stress, deflection, wind, vibration, and lateral forces. However, there is a lack of interactive tools to detect complicated failures and thus address the safety of temporary structures promptly. This paper applies video analysis techniques to concrete shoring and outlines the primary characteristics of automated detection. Shoring failure seriously damages materials and equipment, as well as causing injury or even loss of life among construction crews or members of the public. The suggested approach applies video analysis to characterize the deformation of temporary structures in various failure situations and detect possible failures in early stages of deformation. The method proceeds via two steps: 1) learning and 2) detection of the failure. The first step examines deformation characteristics extracted from video sequences of simulated failure situations. Here, a Hidden Markov Model (HMM) is used to learn and to draw an inference for a possible failure and its cause. The suggested method then incorporates this into comprehensive site inspections and supervision.

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**Keywords:** Video Imaging, Automated Detection, Temporary Structures, Hidden Markov Model

### **Introduction**

Construction is one of the most hazardous industries, and temporary structures feature largely in considerations of construction safety (Culver, 1996). Many temporary structures are erected and dismantled in the course of constructing a new building.

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Temporary structures can be classified into two categories: 1) those that support permanent structures, such as shoring, cofferdams, and formwork; and 2) those that serve as platforms for construction workers, such as scaffolding and ladders. Shoring is a temporary structure that provides support for a permanent structure until it becomes self-supporting and can include steel or timber beams, girders, columns, piles and foundations. Proprietary equipment includes modular shoring frames, post shores, and horizontal shoring. Shoring is also known as falsework. Failures of shoring are usually serious and may lead to significant damage to materials or equipment, collapse, injury, or even loss of life. The various materials that used for temporary structures are often aged and deteriorate rapidly based on their repeated usage. The causes of failures are mainly related to human error, but the imposed loads of structural failures can also be caused by complicated events, accumulated stress, deflection, wind, vibration, and lateral forces.

In this paper, we suggest the application of video analysis techniques to examine the ripple effect of a 1989 bridge failure (Surdahl, Miller, & Glenn, 2010) to determine whether an automated method for discovering and detecting structural failures could address safety concerns related to the use of shoring. There may be a single cause triggering a failure or it may be a combination of several complicated events producing structural deficiencies that lead to the final collapse. However, failures due to complicated causes are seldom recognized before the dramatic event. Federal agencies provide regulations designed to prevent possible failures for temporary structures, and a certified inspector carries out routine inspections manually at regular intervals (Zhu, German, & Brilakis, 2010). However, virtually all of the existing standards were developed for permanent construction, and few specifically address the use of temporary structures in construction (Duntemann, 1996). Inspection results are mainly based on the inspectors' observations after a visual assessment (Zhu, et al., 2010). There is a lack of interactive tools to detect complicated failures and thus address issues related to the safety of temporary structures promptly. Video imaging may be a way to automatically identify and localize specific spatiotemporal patterns that signify structural deficiencies, such as buckling and fracture of shoring tower legs, before a collapse occurs (Ke, Sukthankar, & Hebert, 2007).

This paper suggests an automated method for the detection of possible failures of temporary structures captured in images of specific regions of interest and applied to the learning of defects and training of a Hidden Markov Model (HMM).

By utilizing a video sequence, a time series of frames can be used to construct a histogram image to detect the structural deformation of materials with minimal human intervention. The proposed image processing methods offers a sophisticated way to support comprehensive site monitoring to enhance construction safety and shows promise for further applications on building sites beyond monitoring temporary structures.

## Background

### Learning from a U.S. Bridge Failure

In 1989 the eastbound Maryland Route 198 Bridge over the Baltimore-Washington Parkway suddenly collapsed. Bridges No. 2 and No. 4 passed in parallel over the parkway's southbound lanes, as shown in Figure 1. Researchers inspected all elements for wear and corrosion, including experimental evaluations of individual temporary structures, in this case the tower shoring. It was concluded that construction of shoring and other temporary works were the causes of the collapse. The report evaluated nine possible causes: severe ground vibrations, failure of stay-in-place deck forms, the concrete placement sequence, vehicle damage to shoring, movement of the shoring system from Bridge No. 2 to Bridge No. 4, failure of shoring foundation slabs, the use of hardwood blocking, dynamic loading by the concrete finishing machine, and shoring failure (Surdahl, et al., 2010).



**Figure 1: Collapse of Bridge No. 4 in 1989**

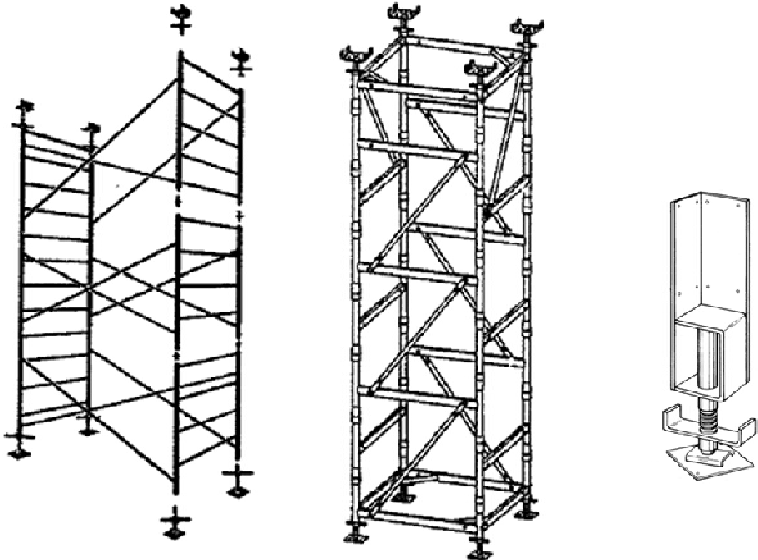
In response to the collapse and to prevent future bridge failures, the Federal Highway Administration (FHWA) immediately launched an investigation, and other agencies joined the effort to learn as much as they could about the cause of the collapse (Surdahl, et al., 2010). Many codes, standards, and regulations provide guidance and ensure the safety of construction. Most standards for temporary structures are voluntary, however, and are generally produced by construction related organizations. For instance, many private industry groups and federal and state organizations, including the Scaffolding, Shoring, and Forming Institute (SSFI), Precast/Prestressed Concrete Institute (PCT), the Federal Highway Administration, American National Standard Institute (ANSI), and so on, have published manuals for temporary structures.

In some cases, these voluntary standards have been adopted either in part or as a whole by regulatory agencies, thereby becoming mandatory standards, but design and construction considerations for temporary structures are usually left to individual engineering judgment (Duntemann, 1996). To reduce unexpected events in construction and enhance safety, a great deal of effort has gone into improving both practices and materials, but construction remains one of the most hazardous industries (Culver, 1996).

### **Types of Shoring and Possible Events**

Shoring can include steel or timber beams, girders, columns, piles and foundations, and any proprietary equipment including modular shoring frames, post shores, and horizontal shoring. Shoring is also known as falsework (Administration, 1993). Currently various types of shoring are available to support imposed loads without excessive stress and deflection and these are generally classified in terms of two types of temporary structure: multistory work and high-clearance construction. In multistory work, an individual tube and a scaffolding type shoring are used to support freshly poured concrete, and a scaffolding type shoring is used for high-clearance construction. Scaffolding shoring is known as tower shoring. Both types of shoring are generally equipped with adjustable jacking tools with which to make vertical adjustments and provide appropriate load endurance. This generally takes the form of a screw leg and is utilized at both the top and bottom of the structure. Fig. 2 shows two different types of tower shoring and screw jack.

The bridge collapse was attributed to nine possible causes, but several of these events could have been recognized prior to the collapse if the inspections of the physical condition had been performed frequently to monitor vehicle damage to the shoring, movement of the shoring system, failure of the shoring foundation slabs, and so on. The researchers found that the cross-bracing members between shoring tower legs had bowed out of plane, making them incapable of providing the bracing needed to support the shoring tower legs when the towers failed (Surdahl, et al., 2010), resulting in buckling and fracture of the shoring tower legs and, ultimately, failure.



**Figure 2: Typical Tower Shoring and Screw Jack**

**Current Practice for Infrastructure Management and Hidden Markov Models**

In the aftermath of structural failures, researchers examine a number of elements to discover the primary causes of failure and the numerous secondary causes that have contributed to that failure. In response to a collapse, and to prevent future similar failures, codes, standards, and regulations are modified to provide better guidance and ensure the safety of structures.

However, in spite of these continuing efforts a great number of structures such as buildings, bridges, and temporary structures continue to fail due to various causes, with the age of the failed structures ranging from one year, or even during the construction process itself, to 157 years (Wardhana & Hadipriono, 2003).

### **Structural Health Monitoring**

Inspecting the structural health of a structure at regular intervals is an important part of efforts to monitor the condition of large structures such as tall buildings and bridges, enabling managers to promptly and quantitatively evaluate their deterioration and any damage that is incurred due to natural hazards and aging. The structural condition is oftentimes described in terms of structural characteristics, but the structures are large and consist of many members that make the assessment of structural condition difficult, inaccurate, and expensive.

The current practice, visual inspection by a highly trained structural engineer, is expensive both in time and cost. For example, the biennial visual inspection of a major bridge such as the Brooklyn Bridge in New York is reported to take over 3 months and costs upwards of \$1 million (Nagayama & Spencer, 2007).

Sensor technology has undergone a process of rapid development in recent years. SHM systems for the assessment and control of structures are now widely used to improve maintenance, increase public safety, and minimize the economic impact of an extreme event. SHM monitors the physical state of a structural system and provides the means for capturing structural response and assessing structural condition.

Because civil structures such as buildings, bridges, and towers are typically large and very complex, an extensive network of sensors is required to accurately assess their structural condition. Most SHM systems are customized for particular structural elements and are therefore not easily scalable for real structures. SHM applications with wireless sensors have greatly reduced the high costs associated with the installation of wired sensors, but the type of wireless smart sensor network needed for applications such as SHM require complex programming, ranging from network functionality to algorithm implementation and must cope with critical issues such as synchronizing sensors and data loss. Most existing SHM methods employ modal analysis to obtain modal parameters such as natural frequencies, damping ratios, and mode shapes (Sohn, Czarnecki, & Farrar, 2000).

Regardless of whether the network is wired or wireless, installing contact-type sensors on structural elements inevitably leads to difficulties with issues such as maintenance, sensor hardware, data aggregation, time synchronization, limited computational capability, the provision of power to the devices, and cost.

In order to address these problems, various vision-based SHM systems have been developed that benefit from the recent rapid advances in computer technology and visualization (Fukuda, Feng, & Shinozuka, 2010). However, the current vision-based systems for displacement measurement are each limited to a single location with a single image-capturing device. Therefore, it is difficult to gather data over sufficient sites to monitor large and complicated structures effectively.

### **Hidden Markov Model**

Real-world processes generally produce servable outputs that can be characterized as signals (Rabinar, 1989). These signals can be classified into groups according to whether they are: 1) discrete or continuous in nature, 2) stationary or non-stationary, and 3) pure or corrupted by other signal sources. A chronological sequence of video images can thus be converted to a signal representing the current condition of a structure as an observable output. Developing an algorithm that depicts a process from these observable outputs to construct a prototype model often works extremely well in practice and makes it possible to create useful practical systems capable of prediction, recognition, or identification in a very efficient manner (Rabinar, 1989). A Hidden Markov Model (HMM) is a statistical Markov Model that is applied to extract probabilistic parameters that contribute to the final output from a mixture of unobserved states and possible observations. Markov processes are often used in models for sequential decision making when outcomes are uncertain (Puterman, 1994). In this case, utilizing a series of structural images for the period leading up to a failure event should provide evidence regarding possible causes for the structural changes that occur near failure, allowing us to simulate these processes, learn through conducting simulations, and develop a prototype model for a future practical application of statistical image diagnosis.

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In this case, if the signals representing possible causes for the bridge collapse are good enough to produce observable outputs, we can simulate the sources, learn through simulations, and develop a prototype model for future applications. Developing an algorithm that depicts a process from the observable outputs to a prototype model often works extremely well in practice and makes it possible to create important practical systems capable of prediction, recognition, or identification in a very efficient manner (Rabiner, 1989).

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## **Proposed Method**

This section briefly describes the proposed approach for detecting possible structural failures of temporary structures. More details are provided in later sections. Video sequences collected with high resolution video cameras are analyzed to detect early symptoms of structural failures caused by various events, such as accumulated stress, deflection, wind, vibration, and lateral forces. These hazardous events tend to deform the materials used for shoring, and thus the ability to detect material deformation as early as possible plays a key role in efforts to prevent the disastrous collapse of a complete structure. The proposed approach consists of two steps: 1) learning and 2) failure detection. In the first step, deformation characteristics of the shoring materials are extracted by analyzing video sequences of simulated failure situations, and then these characteristics are converted into time-dependent signals to train a Hidden Markov Model (HMM). Later, video inputs are processed in the same manner and then fed into the HMM to draw inferences regarding a possible failure and its causes. The overall procedure used for training and detection is summarized in Figure 3, and details of each step are explained in the following subsections.

## **Region of Interest and Edge Detection**

From the first video input frame, a user specifies regions of interest (ROI) that contain shoring materials, which makes video processing much simpler and easier than handling the entire frame to find objects of interest.

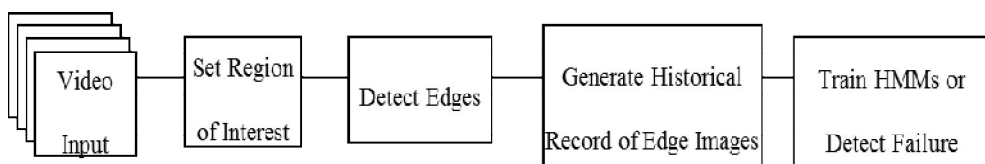


Within the ROIs, simple image processing techniques such as edge detection[9] are applied to extract boundary shape information for the shoring materials and surrounding structures. The edge detection method, one of the fundamental image-based pre-processing procedures, identifies locations where intensity levels in the image change abruptly. Figure 4 depicts an input video frame alongside an image showing the regions of interest and shoring material detected. Note that the shoring materials and their surroundings are extracted as a form of edge image.

### Edge Image History

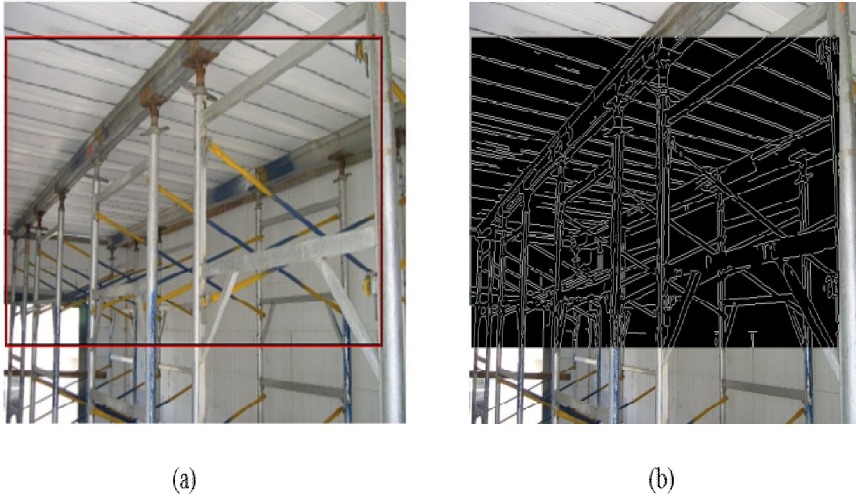
The edge image, extracted in the previous section, provides structural information for the shoring materials and their surrounding structures, even though an explicit analysis has not yet been performed.

As the goal of this task is to detect early symptoms of failure, it is necessary to utilize a video sequence made up of a time series of image frames from which to extract time-varying signals from a series of edge images. A popular technique to achieve this is to construct a histogram image, which is a weighted accumulation of edge images over time. Provided that the camera system is mounted on a sufficiently heavy and rigid body, the histogram image will track changes in the edges caused by only the structure deformation of materials, based on the thickness of the edges.



**Figure 3: Training and Detection Procedure**

For instance, if a shoring pole in Figure 4a is deformed by vertical stress, then the edge image corresponding to the deformed section will change and, accumulated over time, appear to thicken. It is thus straightforward to detect changes in the thickness of the edges by recording the edge histogram images and tracking any variation over time.



**Figure 4:Example of Edge Detection.**

**(a) Input video Frameshowing the ROI. (b) Detected Edges Inside the ROI.**

### Hidden Markov Model Training

Once a suspected abnormality in the edge history image has been detected, its status is tracked using time synchronization. This status consists of location, thickness, center of mass, curvature of outlines, and so on. If an abnormality is confirmed, its features are then quantized and used to create a sequence of outcomes,

$O = O_1O_2O_3O_4\dots$ . Let  $S = \{S_1, S_2, \dots, S_N\}$  a set of states, where  $N$  is the number of distinct states, representing a range from the initial (normal) condition to a near-collapse state. Defining  $q_t$  as the state of HMM at instant for time  $t$ ,  $A = \{a_{ij}\}$  as the state transition probability distribution and  $B = \{b_j(o)\}$  as the observation symbol probability distribution, we can construct a Hidden Markov Model with initial state distribution  $\pi$ . Here,  $a_{ij}$  denotes a transition probability from state  $S_i$  to  $S_j$

$$a_{ij} = P[q_{t+1} = S_j | q_t = S_i], 1 \leq i, j \leq N \quad (1)$$

and  $b_j(o)$  is the probability of observing the symbol  $o$  in state  $S_j$  at instant  $t$ ,

$$b_j(o) = P[o \text{ at } t | q_t = S_j], 1 \leq j \leq N \quad (2)$$

If  $C_k$  is the  $k^{\text{th}}$  type of failure, where  $k=1, 2, \dots, M$ , and  $M$  is the total number of causes of failure, then we simply denote HMM for  $C_k$  as,

$$\lambda_k = (A, B, \pi). \quad (3)$$

For each failure event, CEIs are collected, the feature sequences of the abnormality extracted, and the parameters of HMM  $\lambda_k$  estimated using the Baum-Welch algorithm. The observation probability distribution is assumed to have a multivariate Gaussian distribution. HMM training denotes various factors by a matrix in order to quantize the complicated relationship between abnormal factors.

### Failure Detection

Let  $O = O_1 O_2 O_3 \dots O_T$  an observation sequence for a given time period  $t=1 \dots T$ , where  $N \leq T$ . Given the parameters for HMM per failure event, the probability of the given observation sequence can be calculated, which requires a summation over all possible state sequences. The probability of a state sequence leading to a failure is expressed by the state sequence  $Q = q_1 q_2 q_3 \dots q_N = S_1 S_2 S_3 \dots S_N$ . Then, the probability of the observation sequence given the state sequence  $Q$  and model  $\lambda_k$  is given by,

$$P(O|Q, \lambda_k) = b_{q_1}(O_1) b_{q_2}(O_2) \dots b_{q_N}(O_N) \quad (4)$$

Since the probability of state sequence  $Q$  is given by,

$$P(Q|, \lambda_k) = \pi_k a_{12} a_{23} \dots a_{N-1, N} = \pi_k, \quad (5)$$

the joint probability of both the observation and state sequences occurring is given by,

$$\begin{aligned} P(O, Q| \lambda_k) &= P(O|Q, \lambda_k) P(Q|, \lambda_k) \\ &= b_{q_1}(O_1) b_{q_2}(O_2) \dots b_{q_N}(O_N) \pi_k. \end{aligned} \quad (6)$$

This allows us to compute the probability of a failure event occurring once a sequence of observation has been established and thus issue a warning, along with a failure probability.

The observation sequence is constructed as each observation sample is fed into the HMM models. Each time a sample is obtained the probabilities for each HMM model are computed, allowing continuous monitoring of the structure in real time.

### **Conclusion and Future Work**

This paper proposes an automated method for detecting possible failure events caused by accumulated stress, deflection, wind, vibration, and lateral forces, all of which are known to contribute to structural failures of temporary structures.

Video image processing of a specific region of interest can be used in conjunction with an edge detection method to construct histogram images capable of recognizing changes due to structural deformation. Based on accumulated histograms of the images, abnormality characteristics can be used to train a Hidden Markov Model (HMM) to infer possible failures and their cause. Many construction companies already operate video surveillance systems at construction sites, but their use is generally limited to purposes such as construction updates, security, and monitoring and the protection of high value assets. Recent image processing research and development in the area of automated maintenance and inspection in the construction industry has tended to focus on in-situ object recognition, but this study presents a novel approach to gathering current information and applying it to predict and prevent future disastrous events.

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