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CENTER FOR TRANSPORTATION INFRASTRUCTURE AND SAFETY


# Data Acquisition, Detection and Estimation for Structural Health Monitoring

by

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16. Abstract

This project deals with using a wireless sensor network for structural health monitoring. It includes two objectives: (1) to develop energy-efficient protocols for sensing and communication that are suitable for battery-powered sensor nodes; (2) to develop sampling, detection and estimation algorithms towards timely detection of structural defects and accurate estimation of the damage location on civil structures.

Our activities so far have focused on the second objective| to develop a new measuring methodology and detection algorithms, since the communication protocols rely on the requirement of the algorithms developed in the second part. Specically, we have worked on statistical anomaly detection methods that can find out if there is a defect (such as a crack) in the bridge structure, and if the answer is yes, how to locate the position of the defect.

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# Project Report
# "Data Acquisition, Detection and Estimation for Structural Health Monitoring"

**Maggie X. Cheng**

## 1 Summary of Activities

This project deals with using a wireless sensor network for structural health monitoring. It includes two objectives: (1) to develop energy-efficient protocols for sensing and communication that are suitable for battery-powered sensor nodes; (2) to develop sampling, detection and estimation algorithms towards timely detection of structural defects and accurate estimation of the damage location on civil structures.

Our activities so far have focused on the second objective— to develop a new measuring methodology and detection algorithms, since the communication protocols rely on the requirement of the algorithms developed in the second part. Specifically, we have worked on statistical anomaly detection methods that can find out if there is a defect (such as a crack) in the bridge structure, and if the answer is yes, how to locate the position of the defect.

## 2 Statistical Anomaly Detection Method for Known Loads

There are two kinds of anomalies being considered: (1) data acquisition anomaly, which happens when the measuring device has lost or loosen touch with the structure surface. This type of anomaly will only be observed at the point of measurement and will have no effect on the data collected on other locations; (2) structure health anomaly, such as corrosion at the surface, or cracks on the body of the structure, etc. For the purpose of structure health monitoring, we must be able to distinguish the two types of anomalies.

Our first step is to develop an anomaly detection algorithm for the test mode. In the test mode, the structure is subject to *known* loads. A typical load is a point load moving in constant speed across the whole span of the bridge. While having the point load moving back and forth, samples are taken periodically at the designated locations. The observable data include the dislocation and strain at the sampling points. Through the analysis of the massive collected data, anomaly in the structure can be identified.

Let $X$ stand for the vector of the physical variables, and $Y$ stand for the measurements. For example, if we are considering the dislocations, then $X$ will be the true dislocations based on the dynamics of the system, $Y$ will be the readings from the meters. $Y$ and $X$ have the following relation:

$$y_i = x_i + N_0 + e_i$$

Where $y_i$ and $x_i$ are the $i^{th}$ component of $Y$ and $X$ respectively, corresponding to the $i^{th}$ sampling point, $N_0$ is the Gaussian noise, and $e_i$ is the error, induced by the measuring process or structure anomaly.

Apparently, without the presence of error $e_i$, $y_i$ is not considered abnormal, so $y_i - x_i$ is only white noise with mean 0. Let $z_i = y_i - x_i$. Thus $z_i$ can be viewed as a Gaussian process with zero mean. The problem of anomaly detection can be formulated as a problem of testing the hypothesis of whether the mean vector of a stochastic process is zero. An intuitive method is to simply compute the sample mean and check if the sample mean is zero. The limit of this approach is that the true mean and the sample mean are not the same thing, and we have no control over the accuracy of the detection algorithm.

A more rigorous study we have taken is to compute a threshold value of some test statistics when given an significance level, which represents the probability of incorrectly rejecting a correct hypothesis, i.e., false positive rate. We start from a desired upper bound of false positive rate, and derive the threshold value.

In case of measurement errors, $z_i$'s are independent of each other, so it is relatively easy to compute the threshold value. But in case the errors are induced by the defects on the structure, the errors are correlated, then it is much harder to compute a cutting-off value. The main challenges we have faced are to understand the dependence structure and its impact on the threshold-based anomaly detection method. It is still a work in progress for computing the threshold value.

## 3 Detection of Defects under Unknown Loads

A more realistic, and more challenging problem to solve is when the load on the structure is unknown, and therefore the $X$ vector in the previous section is not given a priori, and $Y$ is the only data available.

We investigated the change-point method, which deals with detecting changes in a process that occur at unknown points in time. The underlying assumption for using this method is that structural defects take place at unknown locations and unknown points in time. Since then, the measurements show abrupt changes in statistical properties of the data. We want to detect the defects as soon as possible while maintaining a tolerable level of false alarms. The algorithm design has a tradeoff component in it between detection delay and false alarm rate.

We modeled the measured data as a time series, and used change-point detection methods to detect at what time the measurement starts to show anomaly. There are several algorithms that have been investigated: the Cumulative sum method, and the SR method. Both methods use preset threshold values. Application of the two methods are straightforward with preset threshold values. Our future work is to compute sharper threshold values in order to reduce the false alarm rate.