# FINITE ELEMENT MODEL UPDATING FOR BRIDGE DEFORMATION MEASUREMENTS EXTRACTED FROM REMOTE SENSING DATA

This document is a technical summary of the project report, *Finite Element Model Updating for Bridge Deformation Measurements Extracted from Remote Sensing Data*, prepared by David Lattanzi for the U.S. DOT Region 3 University Transportation Research Center.

## INTRODUCTION

Accurate and rapid condition assessment of in-service transportation structures is critical for system-wide prioritization decisions. These routine assessments require evaluating a given structure for a variety of defects and aging phenomena, in particular changes in the geometric configuration such as plastic deformations or changes in bearing rotational restraint. Such defects have a direct impact on structural capacity and long-term serviceability. While accurate and quantitative geometric measurements are extremely valuable, they are impractical to collect and leverage using conventional condition assessment methods. In response, three-dimensional (3D) remote sensing has seen expanded interest for the nondestructive evaluation (NDE) of geometric changes, due to the flexibility and improving measurement accuracy of these technologies.

The objective of this research project was to develop and implement a procedure for transforming remotely sensed 3D point clouds, as can be collected through laser scanning or photogrammetric methods, into inputs for numerical engineering simulation tools such as finite element analysis (Figure 1).

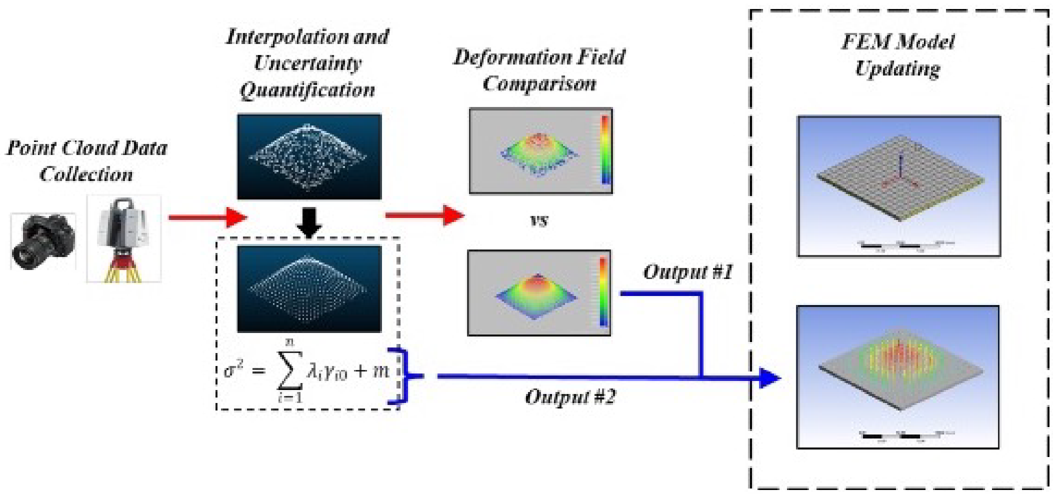


**Figure 1. Process of transforming point cloud data.** Data are first interpolated and measurement error is quantified. These data are then transformed into deformation field measurements derived from the point cloud. In the last step, the data are mapped to a finite element model.

There are several methods to generate dense 3D scans or "point clouds," including terrestrial laser scanning (TLS) and photogrammetry, the process of taking measurements from images [1]. The growing maturity of both of these technologies makes them capable of generating photorealistic and scale-accurate 3D models of bridges with accuracy on the millimeter scale, sufficient for many inspection and evaluation applications. These 3D representations of arbitrary in-situ conditions can currently be used for measurements, volumetric estimation, and change detection [2]–[4]. In most applications, defects are identified by comparing a 3D scan of a damaged structure against a scan taken prior to damage onset. Ideally these defects are then translated into an update of a finite element analysis (FEA) model of a structure for quantitative asset management. Such algorithms would directly support load rating and long-term condition assessment practices by enabling quantitative capacity assessments while providing a foundation for asset owners to make data-driven decisions and prognoses of vulnerable assets.

While methods exist for quantifying 3D deformations from point cloud data [5], they have not been sufficiently evaluated, and the resulting information cannot be leveraged for FEA due to the unstructured nature of the data and complex noise characteristics. More importantly, the resulting measurements of deformation require post-processing before they can be effectively used in a finite element model [6]. The purpose of this project was to develop an analytical pathway that addresses these problems, enables new uses for remote sensing, and provides a basis for rapid and quantitative structural capacity in a manner that currently does not exist.

## METHODOLOGY

The overall algorithmic process developed under this research project is shown in Figure 2. First, point clouds are generated from a collection of images using a photogrammetric structure-from-motion process (SfM) or laser scanning. Local neighborhoods of points are defined for a given point set, defining the statistical basis region for each point in the cloud. The points are then interpolated onto a 3D grid in a manner suitable for accurate finite element model updating. Several interpolators were considered, including ordinary and universal kriging, as well as inverse distance weighting (IDW).

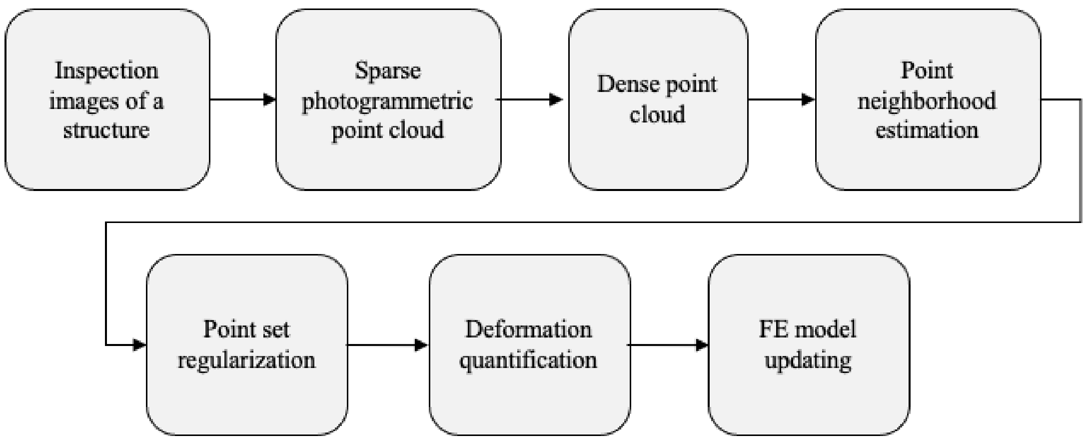


**Figure 2. Algorithmic methodological flowchart.**

Initially, the research team considered the possibility of computing the deformations prior to interpolation. However, by interpolating prior to deformation quantification, the point clouds are effectively smoothed and denoised. This has the carry-on effect of reducing measurement variances and error, and it eliminated the need for more complex and noise-invariant deformation quantification methods.

## DATA SUMMARY

To study the feasibility of the algorithmic process, a series of experimental tests were performed. The focus was on controlled laboratory experiments designed to evaluate the measurement accuracy of the interpolation process. The experiments were designed to simulate plate deformations in a structural component, and the analysis of the associate point clouds. A series of 3D printed specimens were generated (Figure 3). Each specimen represented a deformed plate with a different deformation profile. The purpose of the various deflection patterns was to evaluate the effectiveness of interpolation on a range of deflection geometries and magnitudes.  The knowledge of the surface function for each shape, enabled the isolation of errors from interpolation when compared to the complex sources of errors that can result from the photogrammetric reconstruction process.

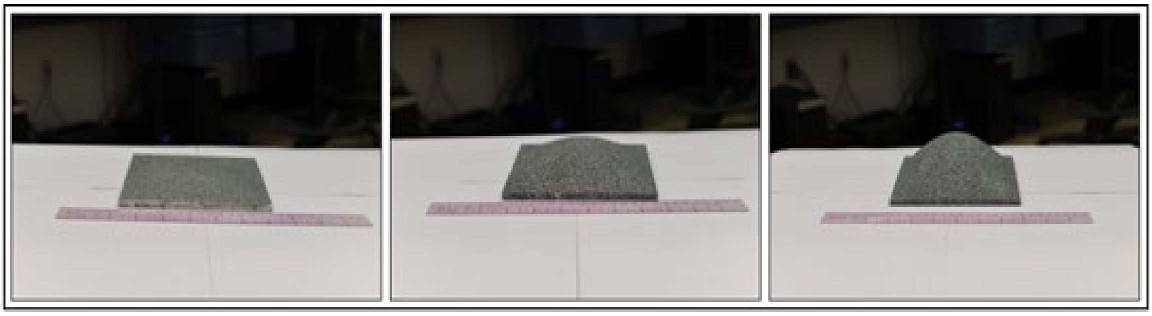

**Figure 3: Examples of printed test specimens.**

**Table 1. Comparative error analysis (RMSE, units of mm) of different interpolation variants. Interpolators included ordinary and universal kriging, as well as inverse distance weighting. Dense cloud refers to a comparison between the uninterpolated point cloud and the ground truth shape profile.**

| Shape # | Dense Cloud | Ordinary Kriging | Universal Kriging | IDW |
|---|---|---|---|---|
| 1 | 1.302 | 1.302 | 1.302 | 1.302 |
| 2 | 0.617 | 0.614 | 0.614 | 0.615 |
| 3 | 0.838 | 0.835 | 0.835 | 0.836 |
| 4 | 0.999 | 0.978 | 0.978 | 0.980 |
| 5 | 0.849 | 0.837 | 0.837 | 0.838 |
| 6 | 0.617 | 0.598 | 0.598 | 0.598 |
| 7 | 0.367 | 0.367 | 0.367 | 0.366 |
| 8 | 0.305 | 0.292 | 0.292 | 0.292 |

## EVALUATION RESULTS

The interpolated results were compared against the ground truth specimen dimensions of each surrogate at each interpolated location. An example result from these tests is shown in Table 1. The results of these experiments indicated that interpolated measurement error was, on average, 0.72 mm when compared to comparisons between the dense point clouds and the functional shape profiles. Differences between ordinary and universal kriging results, as well as with IDW, were negligible. With respect to the comparison of ordinary and universal kriging, the differences were negligible in all cases. Overall, the results indicated that, while the kriging process does induce some measurement error, its impacts are minimal compared to other sources of error in the remote sensing process.

## CONCLUSION AND IMPLEMENTATION

The purpose of this study was to develop a process for transforming point cloud data into a format that can be used for finite element model updating. The core aspect of this process is statistical interpolation through kriging, also known as Gaussian process regression. The development of this process enables consistent and controllable deformation quantification, with reduced distortional noise due to the inherent smoothing that kriging provides. This approach is agnostic to the method of data collection and can be used just as effectively for point clouds collected by laser scanners as it can be used for photogrammetry- or videogrammetry-based point clouds. Experimental analysis of this process showed that kriging maintains the accuracy level of the given point cloud that is used for the observations to make predictions of the deformation values at the target locations. Prior to implementation, future work should evaluate this process at full scale and in a field environment. Such experiments are already planned as of the completion of the project.

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