Monitoring For Underdetermined Underground Structures During Excavation Using Limited Sensor Data

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MONITORING FOR UNDERDETERMINED UNDERGROUND STRUCTURES DURING EXCAVATION USING LIMITED SENSOR DATA

by

NADER MEHDAWI
B.S. University of Benghazi, 2006

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in the Department of Civil, Environmental, and Construction Engineering in the College of Engineering and Computer Science at the University of Central Florida Orlando, Florida

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Major Professor: Hae-Bum Yun
A realistic field monitoring application to evaluate close proximity tunneling effects of a new tunnel on an existing tunnel is presented. A blind source separation (BSS)-based monitoring framework was developed using sensor data collected from the existing tunnel while the new tunnel was excavated. The developed monitoring framework is particularly useful to analyze underdetermined systems due to insufficient sensor data for explicit input force-output deformation relations. The analysis results show that the eigen-parameters obtained from the correlation matrix of raw sensor data can be used as excellent indicators to assess the tunnel structural behaviors during the excavation with powerful visualization capability of tunnel lining deformation. Since the presented methodology is data-driven and not limited to a specific sensor type, it can be employed in various proximity excavation monitoring applications.
I dedicate this work to my beloved family and fiancée
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Motivation

Large amount of tunneling and underground projects are being performed worldwide. Tunnels improve connections and shorten distance. During the last years, the huge demand of underground structures has been consolidated in all countries around the world. The utilization of underground space for storage, power and water treatment plants, civil defense and other activities is often a must in view of limited space, safe operation, environmental protection and energy saving.

According to the Ministry of Land, Transport and Maritime Affairs in Korea, the total road tunnel length in Korea has increased from 150 km (93 miles) to 648 km (403 miles) for the last decade, 332% increased (Ministry of Land, Transport and Maritime Affairs, 2007). Since approximately 70% of the Korean peninsula is mountainous, tunneling cannot be avoided when constructing railroads, high-speed railroads, roads and highways. These factors make the tunneling work complicated in most cases. In order to cope with this demand, there remain several issues for improvement of current tunneling technologies and accurate monitoring system is most important of them especially with limited sensors (In-Mo Lee et al., 2006).

Therefore, systematic monitoring is necessary to these old and new tunnels during their construction or life time. Monitoring can be defined as the use of sensor technologies to characterize a system’s condition, performance or response by using the analytical technique.

Sensor-based continuous monitoring techniques are employed to ensure structural safety during construction. In geotechnical engineering, the monitoring techniques are often used in the
Observational Method after Peck (1969) to collect necessary geotechnical instrumentation measurements to assess the behaviour of the structure during construction; the original design, usually based on most unfavourable assumptions, can be modified for most probable conditions based on the actual measurements for maximum economy and assurance of safety. Structural Health Monitoring (SHM) is another major application of the sensor-based continuous monitoring techniques to detect damage and characterize structural conditions for a wide range of structures in civil, mechanical and aerospace engineering (Doebling et al., 1996; Sohn et al., 2004; Farrar and Worden, 2007).

Apart from the safety issues, economic factors are also important. The fact is that underground structures may have enormous economic impact and appear as the most suitable solution for improving the quality of life in any urban environment, in all corners of the globe. Civil infrastructure systems are generally the most expensive investments in any country and these systems are deteriorating at an alarming rate. For example, in the United States, the Federal Highway Administration reported that nearly 50% of the bridges were built before the 1940’s. A survey in 1996 showed that 42% of the bridges are functionally deficient or obsolete and the cost of correcting all of these deficient bridges exceeds $90 billion. The nationwide maintenance cost for civil infrastructure is estimated at $1.4 trillion. These figures show that there are strong necessities to evaluate the state of the existing infrastructure by regular monitoring (FHWA).

The state of the infrastructure can be predicted or estimated by monitoring. Monitoring also helps in understanding the structure’s performance and in studying the structural response during hazardous or other events which might affect the performance of the structure.
Civil infrastructures undergo a lot of changes in their structural and serviceability characteristics over time. Some of the common reasons for these changes are degradation of material properties, adverse loading and climatic condition, improper maintenance, etc. These changes may be gradual over time or can be sudden due to events like excavation event or earthquakes. (Miriam Heller, 2002)

**Problem Statement**

One of the major concerns arises during underground construction is having insufficient data about the surrounding soil, in other wards: it is underdetermined system. Although some effects of the construction can be observed from the raw sensor data, these observations are qualitative and subjective, and over covered by other dominant effects.

So, the question is; how can limited field sensor data be used to get useful information about the structural behavior change of the surrounding structures? Accidents have great visibility and all efforts have to be done to avoid or minimize their consequences. One way to do so is to monitor the structure closely and use the limited field sources data effectively with good analytical techniques to identify structural behavior, and evaluate their risks.

Under realistic field conditions, one can encounter the following technical challenges in monitoring:

Tunnel failure mechanism can vary depending on construction phases that affect structural capacity and load combination. In addition, since tunnel collapse mechanisms commonly involve brittle failures, it is critical to detect a “small” signature prior to tunnel collapse, which is related to structural failure from sensor datasets. Moreover, tunnel collapse is
usually initiated from localized structural defects. Therefore, spatiotemporal identification of a potential structural failure is critical in tunnel safety monitoring.

Field sensor data are usually influenced with various environmental factors (e.g., ambient temperature and humidity variations) represented as “large” daily, seasonal and yearly trends in sensor time-history data, which cover over the important “small” signature of structural failure. Therefore, to improve the detectability of structural failure, efficient data processing techniques are necessary to decompose the structural failure factors from the environmental factors.

Complex structural behavior of tunnel systems can be expressed using coupled thermo-hydro-mechanical (THM) models: their system input (or force) and system output (or deformation) relations are defined with numerous system parameters associated with a set of interrelated differential equations. In forward analysis, THM models are efficient to estimate structural response for given system parameters and structural excitation conditions. In inverse analysis, however, a large number of sensors should be employed to obtain all necessary the system input-output data in the parameter identification, which results in increasing data acquisition costs. Consequently alternative modeling approaches are desirable in monitoring applications, which do not require explicit relations between the system input and the system output.

**Objective**

The objective of this research study is to develop a monitoring methodology for underdetermined systems using limited response-only data to assess the structure.
The research goal is to be able to detect the structure behavior changes during the construction of underground structures without knowing any information about the forces causing these changes. It is obvious that when such an advanced methodology is realized and applied in the field, the engineers and monitoring agencies of underground work can improve their designs, increase the safety measurement of existing structures and lower the cost of the maintenance by process information in real time. Also the ability to use the technique suggested in this research to a great range of geotechnical analysis problems and not only to underground excavations.

**Approach**

To address the technical challenges of using limited data, a blind source separation (BSS)-based monitoring methodology is presented. Since the methodology is data-driven using response-only sensor data and therefore is not limited to a specific sensor type, it can be used in various tunnel monitoring applications when sensor data are insufficient to determine explicit relations between the input forces and the output responses of tunnel structures. Here, the response-only data are defined as the sensor data measuring the output response or tunnel deformation (e.g., strain, slope, displacement, acceleration, pore water pressures), and the input forces (e.g., service loads, excavation-induced loads, thermal loads) are not used during data processing procedures. Therefore, the monitoring framework presented in this study is particularly designed for the case that one needs to monitor civil engineering structures during construction to evaluate important structural behaviors at different construction phases when the structures are underdetermined due to insufficient sensor data.
In order to demonstrate the feasibility of the monitoring methodology, a real field experimental study of a close proximity tunnel excavation effect on an existing tunnel is presented using respond-only data.

Structure Monitoring System's elements include:

- Limited Deformational Sensory System
- Data acquisition systems
- BSS-PCA Processing Analysis
- Eigen-Parameters Evaluation and Interpretation
- Assess Structural Behavior

Figure 1.1: Methodology illustration
Scope

This study will contain an analytical study for the large field data from real project monitoring a tunnel lining structure in Korea due to excavation of a new tunnel 10 m away. The analytical study will model the data using MATLAB software, applying Principal Component Analysis (PCA) to process and get the pattern of our data. From that model, eigenvalue and eigenvector of the data in study will be drawn. Data interpretation and diagnosis will be done on our result and that will lead into assess the structure behavior.

This research is outlined as follows: literature review on the monitoring methods and principal component analysis are described in chapter 2; Field experimental work is described in chapter 3; The analytical study of the data used in this study are described in chapter 4 with the analysis results; and conclusion and discussed in chapter 5.
2. CHAPTER TWO  
LITERATURE REVIEW

In this chapter, a review of some of the considerable research performed by other researches in the fields related to sensor-based monitoring for tunneling and the effect of tunneling on the surrounding soil and structures. Tunneling causes the surrounding soil react in particular behavior which will affect any nearby tunnel or structures. This chapter will review monitoring techniques for tunnels and soil during the construction or excavation of new tunnel. The discussion will include; Sensor-based technique, Methods, Risk of Tunneling-Induced Damage to Adjacent Tunnels, Data Analysis technique, and Principal Component Analysis. Details of what tunnel-excavation induces to the surroundings will be presented to understand what should be monitored in adjacent existing tunnels.

Sensor-Based Monitoring Techniques for Tunneling

Sensor-based monitoring techniques have been applied to various tunnel applications, and some examples are as follows: Carvalho and Kovári (1977) studied displacement measurements as a mean for safe and economical tunnel design using distometers; Forth and Thorley (1995) reported monitoring study of the ground and buildings affected by the tunnel construction of the Mass Transit Railway in Hong Kong using ground settlement measurements; Inaudi et al. (1998, 1999) evaluated fiber optic sensors for different tunnel types, including a dam tunnel, a cut and cover tunnel, and a Tunnel Boring Machine (TBM) tunnel. Multi-point optical extensometers were applied to measure vault curvature of tunnel linings for short and long-term
monitoring applications; Carnevale et al. (2000) monitored TBM-induced ground vibration using geophones with the sampling frequency at 300 Hz.

Methods of estimating effects associated with tunneling may be classified broadly into three categories; Empirical, Analytical and Numerical. Extensive research on each of these categories is discussed below.

The well-established methods available to date are used primarily to estimate surface settlements in soft ground. The one used most commonly was proposed by Peck (1969), who found that based on a number of field measurements, the surface settlement trough could be represented by a shape of a probability distribution curve, as shown in Equation 2.1:

\[ S = S_{max} \cdot \exp\left(\frac{-x^2}{2i^2}\right) \]  \hspace{1cm} (2.1)

Where:

\( S = \text{Surface settlement at a transverse distance } x \text{ from the tunnel center line} \)

\( S_{max} = \text{Maximum settlement at } x = 0 \)

\( i = \text{Location of maximum settlement gradient or point of inflexion} \)

A significant amount of research involving field observations and model tests has been devoted to the estimation of \( S_{max} \) and \( i \) values for different ground conditions. The estimations of \( i \) values by various researchers are shown in Table 2.1.
<table>
<thead>
<tr>
<th>Name</th>
<th>Expression</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peck (1969)</td>
<td>[ i = \left( \frac{Z_0}{2R} \right)^n ]</td>
<td>Based on field observations. ( n = 0.8 \text{ to } 1.0 )</td>
</tr>
<tr>
<td>Atkinson &amp; Potts (1979)</td>
<td>( i = 0.25(Z_0 + R) ) For dense sand and over consolidated clay ( i = 0.25(1.5Z_0 + 0.5R) )</td>
<td>Based on field observations and model tests</td>
</tr>
<tr>
<td>O’Reilly &amp; New (1982)</td>
<td>For cohesive soil ( i = 0.43Z_0 + 1.1 ) For granular soil ( i = 0.28Z_0 - 0.1 )</td>
<td>Based on field observations of UK tunnels</td>
</tr>
<tr>
<td>Mair (1993)</td>
<td>( i = 0.5Z_0 )</td>
<td>Based on field observations worldwide and centrifuge test</td>
</tr>
<tr>
<td>Attewell (1977)</td>
<td>[ \frac{i}{R} = \alpha \left( \frac{Z_0}{2R} \right)^n ]</td>
<td>Based on field observations of UK tunnels. ( \alpha = 1 \text{ and } n = 1 )</td>
</tr>
<tr>
<td>Clough &amp; Schmidt (1981)</td>
<td>[ \frac{i}{R} = \alpha \left( \frac{Z_0}{2R} \right)^n ]</td>
<td>Based on field observations of US tunnels. ( \alpha = 1 \text{ and } n = 0.8 )</td>
</tr>
</tbody>
</table>

Note: \( Z_0 \) is the depth of tunnel below ground (at tunnel springline) and \( R \) is the tunnel radius
At present, few empirical methods are available to predict subsurface settlement profiles. The two used most widely are those proposed by Mair (1993) and Atkinson and Potts (1979).

These empirical methods do not give highly accurate and reliable results, because they are subject primarily to two important limitations:

- Their applicability to different ground conditions and construction techniques.
- The limited empirical relationships established for prediction.

However, prediction of the effects due to tunneling should take into account the effects of number of parameters. These parameters include:

- The construction method and tunnel driving details
- Tunnel depth and diameter
- Ground water conditions
- The initial stress state
- The stress-strain-strength behavior of the soil around the tunnel excavation
- Environmental variables around the tunnel

Only a few attempts have been made to develop analytical methods that incorporate all factors contributing to ground deformation. Sagaseta (1987) presented closed-form solutions for determining the strain field in initially isotropic and homogeneous incompressible ground due to near surface ground loss caused by tunnel excavation. Verruijt and Booker (1996) presented an analytical solution for tunnels in a homogeneous elastic half space, using an approximate method suggested by Sagaseta (1987) for the case of ground loss. Loganathan and Poulos (1998) modified the Veruijt and Booker solution by incorporating realistic ground loss boundary
conditions that occur during tunnel excavation. An oval shaped gap was introduced at the tunnel crown because ground loss occurs at various stages of excavation. Loganathan and Poulos equations are presented 2.5, 2.6 and 2.7. These solutions predict the tunneling-induced ground movements:

Surface Settlement

\[ U_{Z=0} = \varepsilon_0 R^2 \cdot \frac{4H(1-\nu)}{H^2 + x^2} \cdot \exp\left\{-\frac{1.38x^2}{(H \cot \beta + R)^2}\right\} \quad (2.2) \]

Subsurface Settlement

\[ U_z = \varepsilon_0 R^2 \left( - \frac{z-H}{x^2 + (z-H)^2} + (3-4\nu) \frac{z+H}{x^2 + (z+H)^2} - \frac{2z [x^2 - (z+H)^2]}{[x^2 + (z+H)^2]^2} \right) \cdot \exp\left\{-\frac{1.38x^2}{(H \cot \beta + R)^2} + \frac{0.69 z^2}{H^2}\right\} \quad (2.3) \]

Lateral Deformation

\[ U_x = -\varepsilon_0 R^2 x \left[ \frac{1}{x^2 + (z-H)^2} + \frac{3-4\nu}{x^2 + (z+H)^2} - \frac{4z (z+H)}{[x^2 + (z+H)^2]^2} \right] \cdot \exp\left\{-\frac{1.38x^2}{(H \cot \beta + R)^2} + \frac{0.69 z^2}{H^2}\right\} \quad (2.4) \]

Where:

\( U_{Z=0} = \) ground surface settlement
\( U_z = \) subsurface settlement
\( U_x = \) lateral soil movement
\( R = \) tunnel radius
\( Z = \) depth below ground surface
\( H = \) depth of tunnel axis level
\( \nu = \) Poisson's ratio of soil
\( \varepsilon_0 = \) average ground loss ratio (not a displacement)
\( x = \) lateral distance from tunnel center line
\( \beta = \) Limit angle = 45 + \( \phi/2 \)
These equations allow rapid estimation of ground deformation and require only an estimate of the Poisson's ratio ($\nu$) of the soil. Poisson’s ratio indirectly represents the characteristics of coefficient of lateral earth pressure ($k_0$) value of the ground. The $k_0$ values should be estimated from the relationship (Bowles, 1996) as $k_0 = \frac{\nu}{(1-\nu)}$.

A comparison of the maximum surface settlement and the surface settlement trough width $i$ parameter derived by using various methods and observed values for reported case histories (Loganathan and Poulos, 1998) is shown in Table 2.2.

Table 2.2: Comparison of estimated and observed surface settlement trough parameters

<table>
<thead>
<tr>
<th>Case</th>
<th>Maximum Surface Settlement (mm)</th>
<th>Trough Width, $i$ (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heathrow Express Trial Trunnel, UK</td>
<td>32.5</td>
<td>38.1</td>
</tr>
<tr>
<td>Thunder Bay Tunnel, Canada</td>
<td>49.0</td>
<td>65.6</td>
</tr>
<tr>
<td>Green Park Tunnel, UK</td>
<td>6.0</td>
<td>8.9</td>
</tr>
<tr>
<td>Barcelona Subway Network, Barcelona</td>
<td>29.0</td>
<td>30.3</td>
</tr>
<tr>
<td>Bangkok Sewer Tunnel, Thailand</td>
<td>14.8</td>
<td>21.8</td>
</tr>
</tbody>
</table>

Note: The table shows that the predictions made with equation, empirical predictions and field observations. The case histories reported in Table 2.2 describe only the tunnels excavated through stiff to soft clayey soil.
Soil Parametric Methods

In this section, recent developments of the parametric approaches are reviewed to provide background of parametric soil constitutive modeling. Some of the limitations in empirical and analytical methods may be overcome by the finite element method, which indeed has been used widely for tunneling analyses.

Various constitutive models have been proposed by several researchers to describe various aspects of soil behavior in details and also to apply such models in finite element modeling for geotechnical engineering applications. It must be emphasized here that no soil constitutive model available that can completely describe the complex behavior of real soils under all conditions (Kok Sien Ti et al., 2009)

Mohr-Coulomb Model

Mohr-Coulomb model as shown in Figure (2.1) is an elastic-perfectly plastic model which is often used to model soil behavior in general and serves as a first-order model. In general stress state, the model’s stress-strain behaves linearly in the elastic range, with two defining parameters from Hooke’s law (Young’s modulus, E and Poisson’s ratio, v). There are two parameters which define the failure criteria (the friction angle, \( \phi \) and cohesion, c).
Mohr-Coulomb model is a simple and applicable to three-dimensional stress space model with only two strength parameters to describe the plastic behavior. Regarding its strength behavior, this model performs better. Researchers have indicated by means of true triaxial tests that stress combinations causing failure in real soil samples agree quite well with the hexagonal shape of the failure contour (Goldscheider, 1984). This model is applicable to analyze the stability of dams, slopes, embankments and shallow foundations.

**Modeling Analysis in Tunnels**

The models used for describing soil behavior, whether excavated or not, encompass the following types of theories: linear and non-linear elasticity; elasto-plasticity without strain hardening; elasto-plasticity with strain hardening and elasto-viscoplasticity. Generally speaking, the most widespread constitutive theory is the Mohr-Coulomb perfect elastoplasticity model with
isotropic linear elasticity. Among the elastoplastic theory with strain hardening, the Cam-clay models remains the most widely used.

The findings of various researchers appear contradictory in terms of the selection of appropriate soil models for predicting tunneling-induced ground deformations. Finite element predictions require the following aspects to be modeled accurately:

- The realistic stress path that soil (soil-structure interaction mechanism) experiences during the tunnel excavations for different tunneling methods.
- The three-dimensional effect of various ground loss components, typically face loss and the radial ground loss.
- The stress-strain behavior of the soil around the tunnel.

**Tunneling-Induced Effects on Adjacent Tunnel**

Tunneling-induced ground movement interaction with the adjacent tunnel. The maximum soil movement occurs at or about the tunnel axis level. Relative movements of ground induce bending moments and down-drag forces on close proximity tunnels or any nearby structures. In current practice, the induced effects are estimated using numerical analysis tools, such as the finite element method, the finite difference method and the boundary element method, these tools can provide a comprehensive picture of ground movements throughout the soil around the tunnel and the adjacent structures; however, they rely on appropriate ground models that include soil parameters. In addition, numerical modeling is time consuming and a high level of expertise is required to perform the analysis and the results are not always accurate.
In recent years, many tunneling projects have been built in urban environments which often involve the tunneling of twin tunnels in close proximity to each other. Furthermore, in many cases, the new tunnel is often excavated adjacent to existing tunnels. Hence, the design of new tunnels is crucial to understand the interaction mechanism of the twin tunnels and their effect on the surrounding ground. Furthermore, from the structural engineering point of view, one needs to ensure that excessive bending moments or displacements are not developed in the lining of the tunnel which is built first.

Several researchers observed the interaction occurring between closely spaced tunnels and reported field measurements. Terzaghi (1942), and Ward and Thomas (1965), a set of field instrumentation records on tunnels excavated in Chicago Clay and London Clay indicated that significant lining deformations occurred in the first tunnel as the second tunnel is being excavated causing ground loss toward the tunnel.

Terzaghi (1942) reported a set of field measurements made on tunnels constructed with a center-line spacing of 1.425 tunnel diameters in Chicago Clay and 1.6 tunnel diameters in London Clay respectively. In both cases, the two tunnels were installed consecutively. The measurements indicated that significant liner deformations occurred in the first of the tunnels to be installed as the second tunnel was constructed. The maximum radial displacements, expressed as a percentage of tunnel radiuses, were measured to be 0.10% and 0.12% respectively.

Physical tests were also conducted to investigate the response of the first tunnel’s lining due to the approaching of the second tunnel. Kim et al. (1996 and 1998) performed laboratory tests using a miniature shield to simulate the effect of tunneling on an existing tunnel. The results of their model tests showed that the interaction effects are greatest in the spring-line and crown
of the existing tunnel. However, the interactions between tunnels are unlikely to be significant unless the spacing between the tunnel centerlines is less than about two tunnel diameters (Kim et al., 1996). Additionally, numerical analyses of this interaction problem were carried out by Leca (1989), Addenbrooke and Potts (1996), Yamaguchi et al. (1998). Their results were similar in that; the influence of driving of a second tunnel on the previously installed lining of the first tunnel depends upon relative tunnel position and on the spacing between two tunnels.

Effect of a second tunnel was also found to depend on shield operation. Suwansawat (2004) illustrated that the arrival of the Earth Pressure Balance (EPB) shield used in the construction of twin tunnels in the Bangkok MRTA project can cause outward ground movement during shield passing Figure (2.6). It was found that the maximum outward movement occurred at the position corresponding to the shield tail. In other words, it was affected by tail void grouting. Additionally, the magnitude of outward deformations also appeared to correspond to the magnitude of the applied grouting pressure and the distance from the shield.

Typical numerical analyses of this interaction problem were described by Ghaboussi and Ranken (1977) and Leca (1989). In these studies, a variety of tunnel spacing and procedures to model tunnel construction were adopted. In both cases a two-dimensional approach was used in
which the soil model was elastic. The results indicated that, for the configurations investigated, the computed interactions between two parallel tunnels were small when the center-line spacing was greater than about two tunnel diameters. Addenbrooke and Potts (1996) report numerical analyses of the interaction between two tunnels constructed within a month of each other. These analyses were based on a small strain non-linear soil model. They concluded that the interaction between two adjacent tunnels depends on relative tunnel position (to the side or vertically above) as well as spacing. Driving a new tunnel above an existing tunnel was shown to have significantly less influence on the existing tunnel lining than was the case for equivalent side-by-side tunnels.

**Principal Component analysis**

The Principal Component Analysis (PCA) method, also known as the proper orthogonal decomposition (POD) or the Karhunen-Loève (KL) transform is a multivariate statistical technique often used in exploratory data analysis (Jolliffe, 2002). Some civil engineering applications using PCA can be found in Dai and Lee (2001), Kerschen and Golinval (2002a,b), Folle et al. (2006), Komac (2006), Yun and Reddi (2011), and Masri et al., (2012).

Principal component analysis (PCA) is a mathematical procedure that uses an orthogonal transformation to convert a dataset of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. Its goal is to extract the important information from the data by finding pattern of similarity between the observations.

PCA is an eigenvector-based linear BSS technique that might be the simplest and most popularly used method in this category. Therefore, in this study, PCA is extensively used to
demonstrate the applicability of the BSS-based data processing framework. Two algebraic solutions of PCA are commonly used, including (1) the eigenvector decomposition approach of the correlation matrix and (2) the singular value decomposition approach; the former is described here. For an \((m \times n)\) observation dataset \(X = [x_1; x_2; \ldots; x_m]\), where \(x_i\) is an \((n \times 1)\) vector associated with sensor \(i\), \(m\) is the number of sensors, and \(n\) is the number of data points usually in time, the goal of the algebraic solution is to find the orthogonal matrix of the principal components \(P\), where

\[
Y = PX \ldots
\]

Which renders the correlation matrix \(R_Y\) diagonal. The correlation matrix can be determined from

\[
R_Y = \frac{1}{n-1} Y Y^T = \frac{1}{n-1} P A P^T
\]  

such that

\[
A = X X^T = V \lambda V^T
\]

where \(A\) is an \((m \times m)\) symmetric matrix, \(V\) is the \((m \times m)\) matrix of eigenvectors arranged as column, \(\lambda\) is the \((m \times m)\) diagonal matrix of the eigenvalues. It should be noted that PCA is limited by its global linearity because PCA removes linear correlations based on the second-order statistics of the observed data.

In the classical PCA approach, data normalization is usually required on \(x_i\) for having a zero mean and unitary standard deviation as

\[
x_i = \frac{x_i - \mu_{x_i}}{\sigma_{x_i}}
\]  

(2.8)
where $\mu_{x_i}$ is the sample mean of $x_i$; and $\sigma_{x_i}$ is the sample standard deviation of $x_i$. In structural condition monitoring, however, this normalization process should be avoided since the nominal structural change of interest over time in sensor data $x_i$ will be removed. A discussion related to the PCA normalization can be found in Yan et al. (2007a,b) with geometric interpretation in a two dimensional case.

**Conclusion**

An overview of monitoring techniques; geotechnical; models used and tunnels induced effect with focus on the effect of ground movement and tunneling-induced damage to adjacent tunnels, was presented. In modeling, it is important to choose a soil model which is models the problem being considered. Even with right models, it should be emphasized that there are approximations within the level of accuracy. For example, approximations in the finite element method, approximation in assumptions about the constitutive soil response of the soil and the detailed description of the numerical model and its boundary conditions.

Geotechnical engineers often faces challenges to choose the most appropriate soil model applicable in their numerical modeling. Therefore, the drawback can be summarized as there should be in depth understanding on the concepts, advantages, limitation and also output of each model for each problem being modeled. Engineers should also make use of model which provides a reasonable fit to data obtained from range of laboratory test. It is important to conduct various computation measurement comparisons along with additional full-scale experiments to ascertain the degree of realism in the models in order to adjust and refine them to each type of different modeling application.
In terms of tunneling induced effects, it was concluded that during tunneling soil movement will occur, vertical displacements and lateral displacements. These movements will cause stress increase on nearby structures. In our case, the existing tunnel will be affected by the soil movements influenced by the new tunneling. Figure (2.3) summarized the result of tunneling effect to the surrounding soil and nearby tunnel.

Figure 2.3: Summary of the effect of tunneling on the existing tunnel

The figure summarizes and shows what is expecting to happened due close proximity tunneling. This study will use data-driven technique by implementing Principal Component Analysis method to study the effect of tunneling on close proximity tunnel by using an economical sensing techniques, tilt sensors and displacements sensors.
Ground response mechanism due to tunneling can affect lining of existing tunnels nearby. Therefore, it is clear that the problem of interaction between adjacent tunnels is complex, and the interaction depends on the geometry of the tunnels, the shield operation, lining properties, soil characteristics, and relative stiffness of soil and lining. Operational parameters such as face pressure and grouting pressure are among the most significant factors. Nevertheless, although many studies on the interaction between two tunnels excavated side by side were carried out, very few were based upon field instrumentation and operational parameter records.
3. CHAPTER THREE
EXPERIMENTAL WORK

Site Description

To demonstrate how the aforementioned monitoring methodology can be applied, a realistic railway tunnel construction site was selected: a new tunnel (NT) was excavated adjacent to an old single-track tunnel (OT) in parallel with the ground pillar width of about 10 m (Figure 3.1). A sensor network was installed in a cross-section of OT in its lining direction to observe the NT excavation effects on the OT to monitor structural safety in different phases of the construction.

Figure 3.1: Cross sections of the old (right) and new (left) tunnels (the dimensions are shown in millimeter)

The Goduk OT in Figure (3.1) was originally a single-track railway tunnel constructed in 1981 using the American Steel Support Method (ASSM) between the Ajoong and Sinri Stations on the Jeolla Line owned and operated by the Korail in Korea (Lee et al., 2006). The tunnel dimensions are 1,231 m in length, 5 m in width, and 6.2 m in height, between station (Sta. 30k 285) and (Sta. 31k 516).
In 2008, the NT was constructed in next to the old Goduk OT using the New Austrian Tunneling Method (NATM) as a part of the Jeolla Line double-tracking project. The NT was constructed in parallel to the OT with the soil pillar width of 9 m to 11 m along the whole length. And since the soil pillar is less than the diameter of the new tunnel, it is very critical to know the effect of the excavation of the tunnel on the old tunnel. The dimensions of NT were 1,245 m in length, 11 m in width and 9 m in height, between station (Sta. 30k 285) and (Sta. 31k 516). It was carried out to improve the existing tunnel, Goduk line. Both tunnels’ cross-sections are illustrated in Figure (3.3).

Figure 2 shows the plan and longitudinal views with geological profile of the tunnel site. Since, the geological conditions near the start point were considered weaker than those near the ending point according to a geological survey conducted in 2007 (Park, 2008), monitoring for OT near the starting point was conducted during NT construction.
The start excavation date, of the NT used to demonstrate and evaluate the monitoring methodology in this research, was May 27, 2008. The NT was constructed using the top-heading and bench method. The advance of NT excavation was recorded during construction, and the locations of top-heading and bench excavation fronts are shown in Table 3.1. To measure the effects of NT excavation on OT, an array of sensors was installed at the location of Sta. 30k475 (190 m from the starting point tunnel at Sta. 30k 285). The values in the parenthesis in Table 3.1 are the distance between the top-heading front and the sensor location \(d_t\), and the distance between the bench front and the sensor location \(d_b\). The negative value indicates that the excavation front locates before the sensing location in the direction of excavation, and the positive value indicates that the excavation front locates after the sensing location. The details of the sensor array and instrumentation will be described in the next section.
The NT excavation began on May 27. The top-heading front passed the sensor location on October 2, and the bench front followed the top-heading front on October 30.

Table 3.1: Advances of the new tunnel excavation of top-heading and bench tunneling fronts from the sensing location at OT

<table>
<thead>
<tr>
<th>Dates</th>
<th>Top-heading excavation location (m)</th>
<th>Bench excavation location (m)</th>
<th>Distance (m) b/w top-heading and bench fronts</th>
<th>Note</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008/05/27</td>
<td>0 (-190)</td>
<td>0 (-190)</td>
<td>0</td>
<td>Excavation begun</td>
</tr>
<tr>
<td>2008/08/21</td>
<td>85 (-105)</td>
<td>75 (-115)</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>2008/09/12</td>
<td>147 (-43)</td>
<td>110 (-80)</td>
<td>37</td>
<td>9/12~9/16 holidays</td>
</tr>
<tr>
<td>2008/09/17</td>
<td>147 (-43)</td>
<td>110 (-80)</td>
<td>37</td>
<td></td>
</tr>
<tr>
<td>2008/09/30</td>
<td>188 (-2)</td>
<td>110 (-80)</td>
<td>78</td>
<td></td>
</tr>
<tr>
<td>2008/10/02</td>
<td>199 (+9)</td>
<td>110 (-80)</td>
<td>89</td>
<td>The top heading front passed the sensor location; tunnel visual inspection was conducted (10/2~10/3)</td>
</tr>
<tr>
<td>2008/10/15</td>
<td>224 (+34)</td>
<td>152 (-38)</td>
<td>72</td>
<td></td>
</tr>
<tr>
<td>2008/10/23</td>
<td>252 (+62)</td>
<td>152 (-38)</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>2008/10/28</td>
<td>256 (+66)</td>
<td>180 (-10)</td>
<td>76</td>
<td></td>
</tr>
<tr>
<td>2008/10/30</td>
<td>260 (+70)</td>
<td>190 (0)</td>
<td>70</td>
<td>The bench excavation front reached to the sensor location</td>
</tr>
</tbody>
</table>

Figure 3.3: Illustration of excavation location with dates
Continuous Monitoring for Tunnel Deformation

An array of sensors was installed on OT at the location of Sta. 30k475 (190 m from the starting point tunnel at Sta. 30k 285). The sensor location was selected since it is close to one of nine refuge manholes of OT where tunneling-induced stress would be concentrated due to the reduction of the ground-pillar cross section between OT and NT. To collect necessary data of the OT deformation during NT excavation, a total of 4 extensometers and 4 tilt gauges were installed on OT: for efficient use of the limited number of sensors, the sensors were installed only on the closer side to NT from the crown to the shoulder along the OT’s lining direction (Figure 3).

Figure 3.4: Sensor installation on the old tunnel lining using four extensometers and tilt-meters
The extensometers and tilt gauges were installed at the same locations to measure different kinds of OT lining deformations (Figure 4). The extensometers measured the tunnel displacement in the lining direction: the positive value indicates expansion, and the negative value indicates shrinkage. The tilt gauges measured the slope of the OT lining: the positive value indicates the clockwise slope of the lining with respect to the horizontal direction, and the negative value indicated the counterclockwise slope.

The sensor array was connected to a wireless data acquisition system developed by Kangwon Embedded Software Cooperative Research Center at the Gangneung- Wonju National University in Korea. The sensor data were sampled at 1 sample per 30 minutes for all channels.
Figure 3.6: The sensor locations and sensing directions. Each sensor node consists of one extensometer and on tilt gauge. (The figure is not to scale)
4. CHAPTER FOUR
ANALYTICAL STUDY

Continuous Monitoring Results

The time-history datasets collected with the extensometers and tilt sensors are shown in Figures (4.1) and (4.2), respectively. It was observed that the sensor data were missed between October 10 1:00 AM and October 14 10:00 AM for all sensor nodes due to unpredictable instrument failure. The root mean square (RMS) of each channel was estimated as

$$x_{\text{RMS}} = \sqrt{\frac{1}{n}(x_1^2 + x_2^2 + \cdots + x_n^2)} \quad (4.1)$$

Where: $x_i$ is the $i^{th}$ data point of the sensor measurement. The RMS for the extensometers was between 0.013 mm and 0.095 mm. Since the extensometer length was 800 mm, the corresponding strain in the lining direction was between 0.000016 and 0.000119. The RMS for the tilt gauges was between 0.020 ° and 0.299 °. Therefore, the NT excavation effects on OT lining deformations were not significant.

In Figures (4.1) and (4.2), significant changes were observed from all sensor nodes on September 21. These changes would be due to the event that the location of the top-heading front passed the sensor location during this period (Table 3.1). The second significant changes in most of sensor nodes were observed on October 23. This change would be because the location of the bench excavation front reached to the sensor location in this period (Table 3.1).

Significant daily trends were observed in both the elongation and tilt datasets throughout during the monitoring period. The daily trends are not clearly shown due to their scales in Figure (4.1). The daily trends would be due to environmental fluctuations, but the causes of the daily
trends were not precisely known. Although some effects of the excavation were observed from the raw sensor data, these observations were qualitative and subjective. Technical challenges in assessing the structural behaviors from the raw data include:

The geo-mechanical properties of soil surrounding the OT would change due to soil disturbance during the close proximity excavation. The time-varying characteristics of disturbed soil cannot be identified by applying classical input-output-based inverse analysis models on response-only data.

Since OT was constructed using the ASSM, contact interface between the outer side of the tunnel lining and the surrounding soil is not uniform. Although the stress-strain distribution in the OT’s tunnel lining is largely dependent on the uniformity of soil interface, this information was unknown.

The daily trends observed in both datasets were obviously not due to the NT excavation. For example, although there were no construction activities between September 12 and September 16 due to holidays, the daily fluctuations were still observed. These fluctuations would be due to environmental fluctuations, such as temperature and humidity. Therefore, the relations of the input forces and the output deformations are influenced by the environmental factors as well as the excavation. Modeling these coupling effects is generally very difficult, and for this given monitoring application, the input-output relations are mathematically underdetermined due to insufficient sensor data.

In this chapter, a data-driven signal processing technique using response-only data will be introduced to overcome the above challenges in monitoring when sensor data are limited.
Figure 4.1: Elongation-time histories in the old tunnel lining direction at sensors’ locations and their root mean square (Positive sign means tension)
Figure 4.2: Tilt-time histories in the old tunnel lining direction at sensors’ locations and their root mean square (Positive sign means tilt in clock-wise direction with respect to the horizontal)
Data-Driven Analysis Using Limited Sensor Data

Data-driven analysis is also known as exploratory analysis. It explores the multivariate structure of the data, for one goal which is to identify interesting components. These components would reveal patterns in the data, which are difficult to identify in the raw data. Different data-driven has different identification for their components. For instance, some methods define components as statistically independent; others define them as statistically uncorrelated.

In this section, a data-driven signal processing methodology using response-only data to overcome the challenges in monitoring is introduced, and its analysis results using the deformation data (Tilt and Elongation) is presented.

The blind source separation method is employed to process the response-only data. In the next section, the blind source separation-based data processing framework is described. Also the mathematical description of the principal component analysis method as one kind of the blind source separation methods will be presented in the coming sections. The principal component analysis results are shown and discussed as well.
Blind Source Separation for Underdetermined System

The cause-response system with multiple inputs and multiple outputs is referred to as a MIMO system in Figure (4.3). For a mechanical system, the system inputs are usually causative forces, such as excavation-induced forces or thermal forces; the system outputs are usually responsive deformations, such as displacements, strains, or pore water pressures. In inverse analysis, the system parameters of the MIMO system can be determined when all associated input and output data are available. In field conditions, however, the input and output data that should be collected can be numerous due to various environmental factors; consequently, data collection becomes costly. When the input and output data are insufficient to identify the system parameters, the system is underdetermined.

Figure 4.3: Multiple-Input Multiple-Output system
The blind source separation (BSS), also known as the blind signal separation, is a data-driven technique to separate a set of “source” signals from a set of “mixed” signals with no or little information of the source or mixed signals. Therefore, this technique is useful when the problem is underdetermined due to insufficient sensor data and/or structure information. Respond-only data is used to blind source separation technique, since the data collected are mixed signals of all the sources surrounding the system.

Several source separation techniques can be classified in this category: popular BSS techniques include the principal component analysis (PCA) for statistically uncorrelated multivariate signals, and the independent component analysis (ICA) for statistically independent multivariate signals. General descriptions of PCA and ICA methods can be found in Hyvärinen et al. (2001).

![Blind source separation for MIMO underdetermined system](image)

**Using Principal Component Analysis**

PCA is an eigenvector-based linear BSS technique that might be the simplest and most popularly used method in this category. In this study, it is used for extracting relevant
information in the data set by identifying patterns, and expressing the data in such a way to highlight their similarities and differences. PCA looks for combinations that can be used to summarize data in an understandable way with the option to reduce the number of dimension without much loss of information. Therefore, in this study, PCA is extensively used to demonstrate the applicability of the BSS-based data processing framework presented in this section.

Two mathematical solutions of PCA are commonly used, including (1) the Eigen-decomposition approach of the correlation matrix and (2) the singular value decomposition (SVD) approach; the Eigen-decomposition approach is used in this research.
Analysis Result for Elongation Data

In this section the result of BSS-based monitoring framework presented using the elongation dataset without relying on a priori knowledge the geotechnical properties of the tunnel structures or measuring the input forces data.

PCA was conducted for with 3 days moving window and with 30 minutes time increment, which is the same as the sampling interval. Four sets of eigenvalues $\lambda$ and eigenvectors $V$ were obtained for each time window.

Figure (4.5) shows the changes of the four eigenvalues over time, compared with the distance between the top heading front and the sensor location ($d_t$), and the distance between the bench front and the sensor location ($d_b$) in the same time scale (Table 3.1).

![Figure 4.5: Eigenvalues ($\lambda$) change overtime for elongation](image)
In the legend, M1-M4 represents PCA-modes 1-4 respectively

It is observed that the eigenvalue of Mode 1 ($\lambda_1$) is dominant compared to the other eigenvalues. $\lambda_1$ increased gradually from September 11th to 30th, and it is also observed that,
during that time the top heading excavation is approaching to the sensors location with $d_t$ increased from -43 m to -2 m away from the sensors location while $d_b$ remained at -80 m. After September 30th the top heading excavation passes the sensors location (i.e., $d_t > 0$ m), it is observed that $\lambda_1$ stabilized until October 8th. Between October 2nd and October 23rd, both the top-heading front and the bench front advanced: $d_t$ increased from +9 m to +62 m, and $d_b$ increased from -80 m to -38 m. During this period, the stabilized $\lambda_1$ began slowly increasing again. This change of $\lambda_1$ should be due to the bench excavation, since in this period the bench front became close to the sensor location from $d_b = -80$ m to -38 m, and the top-heading front had passed the sensor location and advanced away from the sensor location to $d_t = +62$ m. When the bench front reached the sensor location on October 30 (i.e., $d_b$ decreased from -38 m to 0 m), $\lambda_1$ increased again after a slight decrease between October 22nd and 24th.

The consistency of the eigenvector ($V$) over time with respect to the eigenvector of the first time window can be calculated using the Modal Assurance Criterion (MAC) as

$$MAC(V_m)_k,(V_m)_1 = \frac{\| (V_m)_k^T (V_m)_1 \|^2}{(V_m)_k^T (V_m)_k (V_m)_1^T (V_m)_1}$$

(4.2)

Where $(V_m)_k$ is the eigenvector of Mode $m$ for the $k^{th}$ time window; $(V_m)_1$ is the eigenvector of Mode $m$ for the first time window; $T$ represents the vector transpose (Maia, 1997). In many applications, two eigenvectors with MAC $\geq 0.8$ are considered to be the same mode shapes. As shown in the Figure (4.6), the MAC of Modes 1, 2 and 3 started decreasing after September 20th, while the MAC of Mode 4 remained consistent.
Figure 4.6: Modal assurance criterion (MAC) values change over-time

In the legend, M1-M4 represents PCA-modes 1-4 respectively.

To visualize the mode shapes of the elongation data in the tunnel lining direction, four corresponding eigenvectors are plotted at different excavation stages in Figure (4.7) using the tunnel cross-section.

It should be noted that the eigenvectors ($V$) of each time window are statistically uncorrelated since they are orthonormal $\|V_1\| = 1$, and $\|V_2\| = 1$, and $V_1 \cdot V_2 = 0$.

Therefore, using the known sensor location coordinates, the eigenvector ($V$) can illustrate the localized spatial information (i.e., mode shape) of the relative elongation deformations at the sensor locations whose magnitude is normalized to 1. The eigenvalue ($\lambda$) represents the magnitude of the corresponding mode shape, which measures the contribution to the total elongational deformation for given time window.
A) September 11th at 23:30

Mode shape 1
$\lambda_1 = 1.23 \times 10^{-4}$

Mode shape 2
$\lambda_2 = 5.95 \times 10^{-5}$

Mode shape 3
$\lambda_3 = 1.91 \times 10^{-6}$

Mode shape 4
$\lambda_4 = 1.03 \times 10^{-6}$

B) September 28th, at 05:00

Mode shape 1
$\lambda_1 = 1.42 \times 10^{-2}$

Mode shape 2
$\lambda_2 = 6.60 \times 10^{-4}$

Mode shape 3
$\lambda_3 = 5.05 \times 10^{-5}$

Mode shape 4
$\lambda_4 = 1.73 \times 10^{-6}$

Figure 4.7: PCA mode shapes for the elongation dataset at different stages (A and B) of the close proximity
Figure 4.8: PCA mode shapes for the elongation dataset at different stages (C and D) of the close proximity excavation.
From Figure (4.7), it is noted that Mode 1 is the dominant mode during the excavation. The eigenvalue ratios of Mode 1 (i.e. $\frac{\lambda_1}{\sum_{i=1}^{n} \lambda_i}$) are:

<table>
<thead>
<tr>
<th>Date</th>
<th>Mode 1 Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>September 11th</td>
<td>0.663</td>
</tr>
<tr>
<td>September 28th</td>
<td>0.952</td>
</tr>
<tr>
<td>October 9th</td>
<td>0.999</td>
</tr>
<tr>
<td>October 31st</td>
<td>0.993</td>
</tr>
</tbody>
</table>

Table 4.1: Mode-1 ratio for elongation

These ratios represent the contributions of the first mode to the total elongational deformation. In addition, it is noted that mode shape 1 and mode shape 2 exchanges the representation on September 28th and September 11th. Mode shape 2 is a secondary mode with eigenvalue ratio and MAC on September 11th of

$$\frac{(\lambda_1)_B}{\sum_{i=1}^{n}(\lambda_i)_B} = 0.044 \quad (4.3)$$

$$MAC_{(V_2)_A,(V_1)_B} = 0.487 \quad (4.4)$$

A significant increase of elongation at the sensor Node 1 in Mode 1 was observed during the during this period

$$\frac{(\lambda_1)_B}{(\lambda_1)_A} = 115.5 \quad (4.5)$$

Where: A and B represent the time windows on September 9th and September 28th, respectively. This change should be due to the effects of the top heading excavation toward the
sensor location since there was no bench excavation activity during this period (refer to Table 3.1).

On October 9th, Mode 1 eigenvalue decreased probably due to soil stabilization after the top heading front passed the sensor location on October 2nd, while the corresponding mode shape remained the same

\[
\frac{(\lambda_1)_C}{(\lambda_1)_B} = 0.902
\]  

\[
MAC(v_1)_C(v_1)_B = 0.99
\]

The eigenvalues of other modes also decreased during this period, and no significant change was observed in their mode shapes.

On October 31st, the stabilized Mode 1 elongation increase again when the bench front reached the sensors location

\[
\frac{(\lambda_1)_B}{(\lambda_1)_C} = 1.583
\]

And

\[
\frac{(\lambda_1)_D}{(\lambda_1)_A} = 164.8
\]

During this period, Mode shape 1 remained the same: MAC((V_1)_D, (V_1)_C) = 0.898. Mode shape 3 on October 9 was observed to become Mode shape 2 on October 31st with increase of its eigenvector due to the effects of the bench excavation: \((\lambda_2)_D/(\lambda_3)_C = 68.8\) and \(MAC((V_2)_D, (V_3)_C) = 0.941\).

**Analysis Result for Tilt Data**

The same PCA procedures in the previous section were applied independently to the tilt dataset to illustrate the presented monitoring methodology is applicable to different sensor types.
This flexibility on sensor types is important in civil engineering monitoring applications, because the selection of sensor types largely varies depending on the associated field conditions of civil engineering structures implementations.

Therefore, the monitoring methodology can be validated by comparing the analysis results of the two independent elongation and tilt data processing implementations.

The same 3-day moving window with a 30 minutes time increment in elongation dataset was applied to the tilt dataset. The PCA eigenvalues for the tilt dataset and the corresponding MAC are shown in Figure (4.8) and Figure (4.9) respectively.

![Figure 4.9: Eigenvalues (\(\lambda\)) changes over-time for tilt](image)

In the legend, M1-M4 represents PCA-modes 1-4 respectively.

Figure (4.8) shows that the Mode 1 eigenvalue (\(\lambda_1\)) is dominant, similar to the results in previous analysis. Eigenvalue \(\lambda_1\) for the tilt dataset increased from September 11th to October 5th as the top-heading front advanced to and passed the sensor location (i.e., \(d_t\) increased). Then, \(\lambda_1\) became stabilized with a slight increment until October 23\(^{rd}\) when the bench front advanced between -38 m < \(d_b\) < -10 m. The peak of \(\lambda_1\) was observed on October 28th, and then it decreased.
Unlike the case of the elongation, the MAC of Modes 1 and 2 were relatively constant over time while those of Modes 3 and 4 fluctuated in Figure (4.9).

Figure 4.10: Mode assurance criteria (MAC) values

To visualize the mode shapes of the tilt data in the tunnel lining direction, four corresponding eigenvectors are plotted at different excavation stages in Figure (4.10) using the tunnel cross-section.
A) September 11th 23:30

Mode 1
\[ \lambda_1 = 3.06 \times 10^{-3} \]

Mode 2
\[ \lambda_2 = 7.90 \times 10^{-4} \]

Mode 3
\[ \lambda_3 = 1.36 \times 10^{-4} \]

Mode 4
\[ \lambda_4 = 1.03 \times 10^{-4} \]

B) September 28th 05:00

Mode 1
\[ \lambda_1 = 1.40 \times 10^{-2} \]

Mode 2
\[ \lambda_2 = 9.37 \times 10^{-4} \]

Mode 3
\[ \lambda_3 = 1.03 \times 10^{-4} \]

Mode 4
\[ \lambda_4 = 8.58 \times 10^{-5} \]

Figure 4.11: The PCA mode shapes for the tilt dataset at different stages (A and B) of the close proximity excavation
Figure 4.12: The PCA mode shapes for the tilt dataset at different stages (C and D) of the close proximity excavation.
The mode shapes with corresponding eigenvalues are illustrated in Figure (4.10). Mode 1 was the dominant mode for all different time windows with eigenvalue ratios \( \frac{\lambda_1}{\sum_{i=1}^{N} \lambda_i} \).

Table 4.2: Mode 1 ratio for tilt

<table>
<thead>
<tr>
<th>Date</th>
<th>Mode 1 ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>September 11th</td>
<td>0.748</td>
</tr>
<tr>
<td>September 28th</td>
<td>0.926</td>
</tr>
<tr>
<td>October 9th</td>
<td>0.995</td>
</tr>
<tr>
<td>October 31st</td>
<td>0.992</td>
</tr>
</tbody>
</table>

The Mode shape 1 for sensor Node 3 Node 3 changed between September 11th and September 28th that resulted in

\[ MAC_{(V_1)_B,(V_1)_A} = 0.566 \]  \hspace{2cm} (4.10)

Then the mode shape remained constant

\[ MAC_{(V_1)_C,(V_1)_B} = 0.848 \]  \hspace{2cm} (4.11)

\[ MAC_{(V_1)_D,(V_1)_C} = 0.998 \]  \hspace{2cm} (4.12)

On September 28th, an increase of the eigenvector was observed in Mode 1

\[ \frac{(\lambda_1)_B}{(\lambda_1)_A} = 4.58 \]  \hspace{2cm} (4.13)

\[ MAC_{(V_1)_B,(V_1)_A} = 0.566 \]  \hspace{2cm} (4.14)

Similarly to the case of the elongation dataset, the increase was due to the tilt at Node 1. The eigenvalue ratio of 4.58, however, it was less significant that the case of elongation dataset (115.5).
On October 9th, the eigenvalue further increased

\[
\frac{(\lambda_1)_C}{(\lambda_1)_A} = 47.7
\]  
\[\text{(4.15)}\]

\[
\frac{(\lambda_1)_C}{(\lambda_1)_B} = 10.4
\]  
\[\text{(4.16)}\]

\[
MAC_{(V_1)_C,(V_1)_B} = 0.848
\]  
\[\text{(4.17)}\]

Therefore, unlike the case of elongation, peak of \(\lambda_1\) was observed after the top heading front passed the sensors location. It was also observed, an apparent rise occurred between September 23rd and 25th which were before the top heading front reached the sensors location. The cause of this rise was unknown from the give construction schedules in Table (3.1).

On October 31st, the Mode 1 eigenvalue decreased after its largest peak was observed on October 26th when bench front advanced from 38 m to 10 m away from the sensors location. The Mode shape 3 on October 9th became Mode shape 2 on October with the increased eigenvalue ration as

\[
\frac{(\lambda_2)_B}{(\lambda_2)_C} = 6.76
\]  
\[\text{(4.18)}\]

**Analysis Result for the Dominant Mode**

The results show that the monitoring methodology can be used for different sensor types since the procedures are solely data-driven. It is also shown that the proximity effects at different excavation stages can be quantified using the eigen-parameters (i.e., eigenvalues and eigenvectors) for both elongation and tilt datasets with strong correlation even though the datasets are processed independently. Since Mode 1 is the only dominant mode for both elongation and tilt datasets, then \(\lambda_1\) and \(V_1\) are further investigated in this section.
The weighted eigenvector can be calculated as $(\lambda_1)_k I (V_1)_k$, where $(\lambda_1)_k$ is the eigenvalue of Mode 1 for time window $k$; $I$ is a $(m \times m)$ identity matrix; $(V_1)_k$ is the $(m \times 1)$ vector of Mode 1 for time window $k$; and $m = 4$ for the number of sensors. Therefore, the weighted eigenvector indicates node deformation in Mode 1.

Figure (4.11) illustrates the time-history plot of weighted eigenvector of Mode 1 for the elongation dataset. The elongation sensor Node 1 located at the tunnel shoulder has the largest deformation over time. It is also observed that the Node 3 sensor has the second largest elongation that is proportional to Node 1 elongation. The Node 4 elongation is inversely proportional to the Node 1 elongation when the top heading and bench fronts reach the sensors location. Consequently, the Node 4 shrinks when Nodes 1 and 3 expand.

Figure (4.12) illustrates the time-history plot of weighted eigenvector of Mode 1 for the tilt dataset. It is observed that the tilt sensor at Node 1 has the dominant change in Mode 1. The peaks of the Node 1 tilt are observed when the top heading and bench fronts reach near the sensors location. The other modes are trivial in terms of their magnitudes.

From the above results, it is found that Node 1 in Mode 1 has the largest deformation for both elongation and tilt datasets. The Node 1 deformation is highly correlated with the excavation proximity distance. No daily fluctuation is observed in the weighted eigenvector time histories. It can be concluded that the mixed effects of the excavation induced deformation and the daily environments-induced deformation in the raw sensor data are effectively decomposed through the PCA procedures, and the Mode 1 weighted eigenvectors in Figure (4.11) and Figure (4.12) shows mostly the excavation-induced deformation.
Figure 4.13: Time-history of the nodal deformation in Mode1 for elongation dataset

Figure 4.14: Time-history of the nodal deformation in Mode1 for tilt dataset
5. CHAPTER FIVE
CONCLUSION

Discussion

The moving window size is an important user-defined parameter of PCA that could influence the performance of the eigenvalue and eigenvector identification in the PCA procedures. The window size of 3 days used in Section 4 was determined based on the temporal consistency of the mode shape that can be measured by the MAC value over time. Since the time-varying deformation of the OT lining at different stages of the NT excavation has to be compared with the initial eigen-parameters as the reference condition, finding the optimal window size for stable initial mode shapes is necessary.

Figure 5.1: Effects of the moving window size on the MAC of Mode 1 with respect to the eigenvector of the first moving window for elongation dataset
Figure 5.2: Effects of the moving window size on the MAC of Mode 1 with respect to the eigenvector of the first moving window for tilt dataset

Figure (5.1) shows the effects of the moving window size on the MAC of the dominant Mode 1 for the elongation and tilt datasets with respect to the eigenvector of the first moving window using MAC equation for $m = 1$. The mode shapes with the moving window sizes smaller than 3 days were not stable as their MAC values decreased immediately as the moving windows progress. MAC became stabilized with the window size of 3 days until the top-heading front advanced close to the sensor location on September 19. However, the moving window size should not be too large since the sensitivity of local temporal events tends to decrease as the window size increases. It is also recommended that the window size is determined with the increment of one day due to the significant daily trends in the sensor measurements. A higher sampling frequency than 2 samples/hour would improve both the MAC consistency and temporal sensitivity for given window length.
Conclusions

A blind source separation (BSS)-based monitoring framework was presented using sensor data collected in a realistic field experiment of close proximity tunneling effects on an existing tunnel. The presented monitoring framework is particularly useful to analyze underdetermined systems due to insufficient sensor data for explicit input-output relations. Since the presented monitoring methodology is data-driven and not limited to a specific sensor type, it is flexible to be used in various proximity excavation monitoring applications.

In the underdetermined case, measuring the output response is more advantageous than measuring the input forces since the latter does not contain the information of the system characteristics change over time during construction, while the former does contain such information; that is, the output response data are affected by both the input force and the system characteristics. However, a technical challenge with the response data is to analyze the complicated linear or nonlinear convolutional effects of the input force and the system characteristics in the output response data (Yun and Reddi 2011).

The principal component analysis (PCA) was employed to decompose the “mixed” raw response data into a linear combination of statistically uncorrelated mode shapes of “source” data. The PCA results for elongation and tilt datasets show that the eigen-parameters can be used as excellent indicators to assess the tunnel structural behaviors during the excavation. The eigenvector represents the localized spatial information of relative deformations at the sensor locations whose magnitude is normalized to 1. The eigenvalue represents the contribution to total deformation for given time window. The weighted eigenvector time histories showed a strong correlation with the proximity of the top-heading and bench fronts to the sensor location,
while no daily fluctuation was observed in those time histories. Since the excavation-related events and the daily environment-related events are likely statistically uncorrelated, the deformations induced by these two events would not be observed in a same mode.

The PCA eigen-parameters, however, are not uniquely related to mechanical properties (e.g., stiffness and damping constants) since the mathematical formulation of PCA is not based on the explicit input-output relationship. Instead, PCA decomposes the orthonormal patterns from multivariate deformation vectors. Therefore, the eigen-parameters could be affected by changes in the input forces and/ or the mechanical properties. Consequently, the PCA eigen-parameters obtained from the response-only data are useful in monitoring applications for construction and operation where one has to monitor both excessive force levels and structural damages with a small number of sensors. If one has to uniquely identify mechanical properties, additional sensors are needed to measure the input forces. The presented monitoring methodology is useful for ad hoc analysis for underdetermined systems when many sensors cannot be used during tunnel excavation. The detection of an anomalous change in the eigen-parameters during construction would be useful information to conduct costly, but more rigorous post hoc analysis with material testing or monitoring with additional sensors (Yun et al. 2012).
APPENDIX: MATLAB CODE

clear all; clc;

% FILE SETUP
SrcFileName{1} = 'Node02.raw';
SrcFileName{2} = 'Node03.raw';
SrcFileName{3} = 'Node04.raw';
SrcFileName{4} = 'Node05.raw';

% CHANNEL SETUP
DateStr1 = '2008/09/09 00:00:00';
DateStr2 = '2008/11/01 00:00:00';
TimeWindowVec = [0 0 0 30 0];
Fsam = 48;

% TIME WINDOW SETUP
TiltUnit = 'Deg';
DispUnit = 'mm';
TempUnit = 'Degree-Celcius';
LocalTimeZone = 'Seoul';
DayLightSaving = 0;
LocalTimeDifference = 9;
WinLen = 4*Fsam;

% PCA SETUP
PCAType = 'COR';
PCAChNum = [2 3 4 5];

% FLAG SETUP
FL(1) = 1;
FL(2) = 1;
FL(3) = 1;
FL(4) = 1;
FL(5) = 1;
FL(6) = 1;
FL(7) = 1;
FL(8) = 1;
FL(9) = 1;
FL(10)= 1;
FL(11)= 1;

PWD = pwd;
SrcDir = sprintf('%s%s%s',PWD,filesep,'Sig');
SrcFilePath{1} = sprintf('%s%s%s',SrcDir,filesep,SrcFileName{1});
MLen = length(SrcFileName);
for M = 1:MLen,
    CurFilePath = sprintf('%s%s%s',SrcDir,filesep,SrcFileName(M));
    FID = fopen(CurFilePath,'r');

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Lines = textscan(FID, '%19c\t%10c\t%f\t%f');
DateFormat = 'yyyy/mm/dd HH:MM:SS';
DateNum = datenum(DateNum, DateFormat);
Time.DateNum{M} = DateNum;
Node = Lines{2};
DispVec = Lines{4};
TiltVec = Lines{5};
Disp{M} = DispVec;
Tilt{M} = TiltVec;

end
Tilt{1} = -Tilt{1};
Tilt{2} = -Tilt{2};

for M = 1:MLen,
    CurDateStr = DateStr1;
    CurDateNum = datenum(CurDateStr, DateFormat);
    CurDateVec1 = datevec(CurDateNum);
    CurDateVec2 = DateStr2;
    CurTimeWindowDateVec = CurDateVec1;
    CurTimeWindowDateNum = datenum(CurDateVec1);
    TimeWindowDateNum1 = datenum(CurDateVec1);
    while CurTimeWindowDateNum < datenum(CurDateVec2),
        CurTimeWindowDateVec = CurTimeWindowDateVec + TimeWindowVec;
        CurTimeWindowDateNum = datenum(CurTimeWindowDateVec);
        TimeWindowDateNum1 = [TimeWindowDateNum1; CurTimeWindowDateNum];
    end
    TimeWindowDateNum{M} = TimeWindowDateNum1;
    clear TimeWindowDateNum1;
end
KLen = length(TimeWindowDateNum{1});
KLen2 = KLen - 2;

IdxMat = [];       % Cummulative window
IdxMat1 = [];      % Moving window
TimeMat = [];
TiltMat = [];
DispMat = [];
WinTimeEndCluster = [];
WinTimeIncrement = [];

for K = 1:KLen-1    % Cummulative time window
    for M = 1:MLen  % Sensor node
        CurTimeWindowIdx{K}{M} = find(Time.DateNum{M}>=TimeWindowDateNum{M}{K}) &
            Time.DateNum{M}<TimeWindowDateNum{M}{K+1});
        if isempty(CurTimeWindowIdx{K}{M}),
            CurTimeWindow{K}{M} = NaN;
            Win.Time.Index{K}{M} = NaN;
            Win.Time.DateNum{K}{M} = NaN;
            Win.Disp.Sig{K}{M} = NaN;
            Win.Tilt.Sig{K}{M} = NaN;
        else
            CurTimeWindow{K}{M} = Time.DateNum{M}(CurTimeWindowIdx{K}{M});
            Win.Time.Index{K}{M} = CurTimeWindowIdx{K}{M};
            Win.Time.DateNum{K}{M} = CurTimeWindow{K}{M};
            Win.Disp.Sig{K}{M} = Disp{M}(CurTimeWindowIdx{K}{M});
            Win.Tilt.Sig{K}{M} = Tilt{M}(CurTimeWindowIdx{K}{M});
        end
    end

%---
Win.Time.Start.DateNum{K}{M} = TimeWindowDateNum{M}(K);
Win.Time.Start.DateVec{K}{M} = datevec(TimeWindowDateNum{M}(K));
Win.Time.Start.DayOfWeek{K}{M} = weekday(TimeWindowDateNum{M}(K));
Year = year(TimeWindowDateNum{M}(K));
Month = month(TimeWindowDateNum{M}(K));
Day = day(TimeWindowDateNum{M}(K));
Win.Time.Start.DayOfYear{K}{M} = daysact(datenum([Year 1 1]),datenum([Year Month Day]));
Win.Time.Start.DST{K}{M} = DayLightSaving;
%---
Win.Time.End.DateNum{K}{M} = TimeWindowDateNum{M}(K+1);
Win.Time.End.DateVec{K}{M} = datevec(TimeWindowDateNum{M}(K+1));
Win.Time.End.DayOfWeek{K}{M} = weekday(TimeWindowDateNum{M}(K+1));
Year = year(TimeWindowDateNum{M}(K+1));
Month = month(TimeWindowDateNum{M}(K+1));
Day = day(TimeWindowDateNum{M}(K+1));
Win.Time.End.DayOfYear{K}{M} = daysact(datenum([Year 1 1]),datenum([Year Month Day]));
Win.Time.End.DST{K}{M} = DayLightSaving;
%---
Win.Time.TimeIncrement{K}{M} = 1800; % Sampling interval: 30 minutes
Win.Time.LocalTimeZone{K}{M} = LocalTimeZone;
Win.Time.LocalTimeDifference{K}{M} = LocalTimeDifference;
%---
end
IdxMat = [IdxMat; cell2mat(Win.Time.Index{K})];
CumWin.Time.Index{K} = IdxMat;
TimeMat = [TimeMat; cell2mat(Win.Time.DateNum{K})];
CumWin.Time.DateNum{K} = TimeMat;
DispMat = [DispMat; cell2mat(Win.Disp.Sig{K})];
CumWin.Disp.Sig{K} = DispMat;
TiltMat = [TiltMat; cell2mat(Win.Tilt.Sig{K})];
CumWin.Tilt.Sig{K} = TiltMat;
end

for K = 1:KLen-WinLen, % Moving time window
IdxMat = [];
TimeMat = [];
DispMat = [];
TiltMat = [];
for KK = 0:WinLen-1
IdxMat = [IdxMat; cell2mat(Win.Time.DateNum{K+KK})];
MovWin.Time.Index{K} = IdxMat;
TimeMat = [TimeMat; cell2mat(Win.Time.DateNum{K+KK})];
MovWin.Time.DateNum{K} = TimeMat;
DispMat = [DispMat; cell2mat(Win.Disp.Sig{K+KK})];
MovWin.Disp.Sig{K} = DispMat;
TiltMat = [TiltMat; cell2mat(Win.Tilt.Sig{K+KK})];
MovWin.Tilt.Sig{K} = TiltMat;
end
end

%--- Principal Component Analysis ---
% PCA for Tilt
Sig = [];
for K = 1:length(MovWin.Time.DateNum)
Sig = MovWin.Tilt.Sig{K};
if ~isnan(sum(Sig))
    Cov = cov(Sig,1);
    switch lower(PCAType)
        case 'cov'
            [Proj,EigVec,EigVal] = pca1(Sig);
        case 'cor'
            [Proj,EigVec,EigVal] = pca2(Sig',zeros(size(Sig,2),1));
    end
    MovWin.PCA.Type = PCAType;
    MovWin.PCA.Tilt.Time.Index(K) = MovWin.Time.Index(K);
    MovWin.PCA.Tilt.Time.Start.DateNum(K) = MovWin.Time.DateNum(K)(1,:);
    MovWin.PCA.Tilt.Time.End.DateNum(K) = MovWin.Time.DateNum(K)(end,:);
    MovWin.PCA.Tilt.Cov{K} = Cov;
    if EigVec(1,1) < 0, EigVec(:,1) = -EigVec(:,1); end
    if EigVec(1,2) < 0, EigVec(:,2) = -EigVec(:,2); end
    if EigVec(1,3) < 0, EigVec(:,3) = -EigVec(:,3); end
    if EigVec(1,4) < 0, EigVec(:,4) = -EigVec(:,4); end
    MovWin.PCA.Tilt.EigVec{K} = EigVec;
    MovWin.PCA.Tilt.Proj{K} = Proj;
    MovWin.PCA.Tilt.EigVal{K} = EigVal;
    MovWin.PCA.Tilt.EigValRat{K} = EigVal/sum(EigVal);
    MovWin.PCA.Tilt.ChNum{K} = PCAChNum;
else
    MovWin.PCA.Type = PCAType;
    MovWin.PCA.Tilt.Index(K) = MovWin.Time.Index(K);
    MovWin.PCA.Tilt.Time.DateNum(K) = MovWin.Time.DateNum(K);
    MovWin.PCA.Tilt.Time.Start.DateNum(K) = MovWin.Time.DateNum(K)(1,:);
    MovWin.PCA.Tilt.Time.End.DateNum(K) = MovWin.Time.DateNum(K)(end,:);
    MovWin.PCA.Tilt.Cov{K} = nan(length(PCAChNum));
    MovWin.PCA.Tilt.EigVec{K} = nan(length(PCAChNum));
    MovWin.PCA.Tilt.Proj{K} = nan(size(Sig));
    MovWin.PCA.Tilt.EigVal{K} = nan(length(PCAChNum),1);
    MovWin.PCA.Tilt.EigValRat{K} = nan(length(PCAChNum),1);
    MovWin.PCA.Tilt.ChNum{K} = PCAChNum;
end
end
% MAC for Tilt
for K = 1:length(MovWin.Time.DateNum),
    for M = 1:length(PCAChNum)
        MovWin.PCA.Tilt.MAC(K,M) = MAC(MovWin.PCA.Tilt.EigVec{1}(:,M),MovWin.PCA.Tilt.EigVec{K}(:,M));
    end
end
% PCA for Displacement
Sig = [];
for K = 1:length(MovWin.Time.DateNum)
    Sig = MovWin.Disp.Sig{K};
    if ~isnan(sum(Sig))
        Cov = cov(Sig,1);
        switch lower(PCAType)
            case 'cov'
                [Proj,EigVec,EigVal] = pca1(Sig);
            case 'cor'
                [Proj,EigVec,EigVal] = pca2(Sig',zeros(size(Sig,2),1));
        end
    end
end
MovWin.PCA.Disp.Index{K} = MovWin.Time.Index{K};
MovWin.PCA.Disp.Time.DateNum{K} = MovWin.Time.DateNum{K};
MovWin.PCA.Disp.Time.Start.DateNum{K} = MovWin.Time.DateNum{K}(1,:);
MovWin.PCA.Disp.Time.End.DateNum{K} = MovWin.Time.DateNum{K}(end,:);
MovWin.PCA.Disp.Cov{K} = Cov;
if EigVec(1,1) < 0, EigVec(:,1) = -EigVec(:,1); end
if EigVec(1,2) < 0, EigVec(:,2) = -EigVec(:,2); end
if EigVec(1,3) < 0, EigVec(:,3) = -EigVec(:,3); end
if EigVec(1,4) < 0, EigVec(:,4) = -EigVec(:,4); end
MovWin.PCA.Disp.EigVec{K} = EigVec;
MovWin.PCA.Disp.Proj{K} = Proj;
MovWin.PCA.Disp.EigVal{K} = EigVal;
MovWin.PCA.Disp.EigValRat{K} = EigVal/sum(EigVal);
MovWin.PCA.Disp.ChNum{K} = PCAChNum;
else
MovWin.PCA.Disp.Index{K} = MovWin.Time.Index{K};
MovWin.PCA.Disp.Time.DateNum{K} = MovWin.Time.DateNum{K};
MovWin.PCA.Disp.Time.Start.DateNum{K} = MovWin.Time.DateNum{K}(1,:);
MovWin.PCA.Disp.Time.End.DateNum{K} = MovWin.Time.DateNum{K}(end,:);
MovWin.PCA.Disp.Cov{K} = nan(length(PCAChNum));
MovWin.PCA.Disp.EigVec{K} = nan(length(PCAChNum));
MovWin.PCA.Disp.EigVal{K} = nan(length(PCAChNum),1);
MovWin.PCA.Disp.EigValRat{K} = nan(length(PCAChNum),1);
MovWin.PCA.Disp.ChNum{K} = PCAChNum;
end

% MAC for Tilt
for K = 1:length(MovWin.Time.DateNum),
    for M = 1:length(PCAChNum)
        MAC(MovWin.PCA.Disp.EigVec{1}(:,M),MovWin.PCA.Disp.EigVec{K}(:,M))
    end
end

%-- Plotting ---
if FL(1) % Tilt time histories
    figure(1)
    subplot(4,1,1);
    plot(Time.DateNum{1},Tilt{1},'b-','LineWidth',1);
    datetick('x','mm/dd'); xlab('Time'); ylab('Tilt 1'); grid on; ylim([-1 1])
    subplot(4,1,2);
    plot(Time.DateNum{2},Tilt{2},'b-','LineWidth',1);
    datetick('x','mm/dd'); xlab('Time'); ylab('Tilt 2'); grid on; ylim([-0.1 0.1])
    subplot(4,1,3);
    plot(Time.DateNum{3},Tilt{3},'b-','LineWidth',1);
    datetick('x','mm/dd'); xlab('Time'); ylab('Tilt 3'); grid on; ylim([-0.2 0.2])
    subplot(4,1,4);
    plot(Time.DateNum{4},Tilt{4},'b-','LineWidth',1);
    datetick('x','mm/dd'); xlab('Time'); ylab('Tilt 4'); grid on; ylim([-0.1 0.1])
end

%-- if FL(2) % Enlongation time histories
```matlab
subplot(4,1,1);
plot(Time.DateNum{1},Disp{1},'k-','LineWidth',1.5);
datetick('x','mm/dd'); xlabel('Time'); ylabel('Extensometer 1'); grid on;
ylim([-0.2 0.1])
subplot(4,1,2);
plot(Time.DateNum{2},Disp{2},'k-','LineWidth',1.5);
datetick('x','mm/dd'); xlabel('Time'); ylabel('Extensometer 2'); grid on;
ylim([-0.04 0.02])
subplot(4,1,3);
plot(Time.DateNum{3},Disp{3},'k-','LineWidth',1.5);
datetick('x','mm/dd'); xlabel('Time'); ylabel('Extensometer 3'); grid on;
ylim([-0.1 0.05])
subplot(4,1,4);
plot(Time.DateNum{4},Disp{4},'k-','LineWidth',1.5);
datetick('x','mm/dd'); xlabel('Time'); ylabel('Extensometer 4'); grid on;
ylim([-0.05 0.05])
end

if FL(3) % Moving-window Tilt PCA change
    figure(3)
    subplot(3,1,1)
    T = cell2mat(MovWin.PCA.Tilt.Time.End.DateNum);
    T = reshape(T,MLen,length(MovWin.Time.DateNum)); T = T';
    semilogy(T(:,1),cell2mat(MovWin.PCA.Tilt.EigVal)', 'LineWidth',1.5);
    datetick('x','mm/dd'); xlabel('Time'); ylabel('Eigenvalue (Log)'); grid on;
    title('Moving-Window Tilt PCA Eigenvalue')
    subplot(3,1,2)
    plot(T(:,1),cell2mat(MovWin.PCA.Tilt.EigValRat)', 'LineWidth',1.5);
    datetick('x','mm/dd'); xlabel('Time'); ylabel('Eigenvalue (%)'); grid on;
    ylim([-0.1 1.1])
    subplot(3,1,3)
    plot(T(:,1),MovWin.PCA.Tilt.MAC,'LineWidth',1.5);
    datetick('x','mm/dd'); xlabel('Time'); ylabel('MAC'); grid on; ylim([0 1.1])
end

if FL(4) % Moving-window Elongation PCA change
    figure(4)
    subplot(3,1,1)
    T = cell2mat(MovWin.PCA.Disp.Time.End.DateNum);
    T = reshape(T,MLen,length(MovWin.Time.DateNum)); T = T';
    semilogy(T(:,1),cell2mat(MovWin.PCA.Disp.EigVal)', 'LineWidth',1.5);
    datetick('x','mm/dd'); xlabel('Time'); ylabel('Eigenvalue (Log)'); grid on;
    %ylim([10^-8 1])
    title('Moving-Window Displacement PCA Eigenvalue')
    subplot(3,1,2)
    plot(T(:,1),cell2mat(MovWin.PCA.Disp.EigValRat)', 'LineWidth',1.5);
    datetick('x','mm/dd'); xlabel('Time'); ylabel('Eigenvalue (%)'); grid on;
    ylim([-0.1 1.1])
    subplot(3,1,3)
    plot(T(:,1),MovWin.PCA.Disp.MAC,'LineWidth',1.5);
    datetick('x','mm/dd'); xlabel('Time'); ylabel('MAC'); grid on; ylim([0 1.1])
end

if FL(5)
    figure(5)
    T = cell2mat(MovWin.PCA.Tilt.Time.End.DateNum);
    T = reshape(T,MLen,length(MovWin.Time.DateNum)); T = T';
```
% Cumulative Tilt PCA MAC
plot(T,MovWin.PCA.Tilt.MAC,'LineWidth',1.5);
datetick('x','mm/dd'); xlabel('Time'); ylabel('MAC'); grid on;
title('Cumulative Tilt PCA MAC')
end

---
if FL(6)
    figure(6)
    K = 1;
    TimeStamp = MovWin.Time.DateNum{K}(1,1);
    if isnan(TimeStamp)
        TimeStamp = 'NaN';
    else
        TimeStamp = datestr(TimeStamp,'yyyy/mm/dd HH:MM:SS');
    end
    fprintf('TIMESTAMP: %s \n',TimeStamp)
    for M = 1:4
        subplot(1,4,M)
        X = [0:0.01:-1];
        Y = sqrt(1-X.^2);
        plot(X,Y,'k--'); hold on
        I = 1;
        for Deg = [0, pi/8, pi/4, pi*3/8]
            R = 1;
            L = sqrt(2)*R*sin(Deg);
            PTS(I,1) = -R + sin(Deg/2)/sin(pi/2)*L;
            PTS(I,2) = 0 + sin((pi-Deg)/2)/sin(pi/2)*L;
            plot(PTS(I,1),PTS(I,2),'ko'); I = I + 1;
        end
        I = 1; Scale = 0.2;
        for Deg = [0, pi/8, pi/4, pi*3/8]
            R = 1+Scale*MovWin.PCA.Disp.EigVec{K}(1,M);
            L = sqrt(2)*R*sin(Deg);
            PTS1(I,1) = -R + sin(Deg/2)/sin(pi/2)*L;
            PTS1(I,2) = 0 + sin((pi-Deg)/2)/sin(pi/2)*L;
            plot(PTS1(I,1),PTS1(I,2),'rs'); I = I + 1;
        end
        line([PTS1(1,1),PTS1(2,1)], [PTS1(1,2),PTS1(2,2)], 'LineStyle','--', 'Color','b');
        line([PTS1(2,1),PTS1(3,1)], [PTS1(2,2),PTS1(3,2)], 'LineStyle','--', 'Color','b');
        line([PTS1(3,1),PTS1(4,1)], [PTS1(3,2),PTS1(4,2)], 'LineStyle','--', 'Color','b');
        hold off
        xlim([-1.2 0]); ylim([0 1.2]);
        title(sprintf('Elongation - Mode %d',M))
        line([PTS(1,1),PTS1(1,1)], [PTS(1,2),PTS1(1,2)], 'LineStyle','--', 'Color','k');
        line([PTS(2,1),PTS1(2,1)], [PTS(2,2),PTS1(2,2)], 'LineStyle','--', 'Color','k');
        line([PTS(3,1),PTS1(3,1)], [PTS(3,2),PTS1(3,2)], 'LineStyle','--', 'Color','k');
        line([PTS(4,1),PTS1(4,1)], [PTS(4,2),PTS1(4,2)], 'LineStyle','--', 'Color','k');
end
if FL(7)
  figure(7)  % Tilt Modeshapes
  K = 1;  % Window number
  TimeStamp = MovWin.Time.DateNum(K)(1,1);
  if isnan(TimeStamp)
    TimeStamp = 'NaN';
  else
    TimeStamp = datestr(TimeStamp,
      'yyyy/mm/dd HH:MM:SS');
  end
  fprintf('
TIMESTAMP: %s
',TimeStamp)
  for M = 1:4
    subplot(1,4,M)
    X = [0:-0.01:-1];
    Y = sqrt(1-X.^2);
    plot(X,Y,'k--'); hold on
    I = 1;
    for Deg = [0, pi/8, pi/4, pi*3/8]
      R = 1;
      L = sqrt(2)*R*sqrt(1-cos(Deg));
      PTS(I,1) = -R + sin(Deg/2)/sin(pi/2)*L;
      PTS(I,2) = 0 + sin((pi-Deg)/2)/sin(pi/2)*L;
      plot(PTS(I,1),PTS(I,2),'ko');
      I = I + 1;
    end
    I = 1; Scale = 0.2; %/max(abs(CumWin.PCA.Disp.EigVec{1}(:,M)));
    for Deg = [0, pi/8, pi/4, pi*3/8]
      R = 1+Scale*MovWin.PCA.Tilt.EigVec(K)(I,M);
      L = sqrt(2)*R*sqrt(1-cos(Deg));
      PTS1(I,1) = -R + sin(Deg/2)/sin(pi/2)*L;
      PTS1(I,2) = 0 + sin((pi-Deg)/2)/sin(pi/2)*L;
      plot(PTS1(I,1),PTS1(I,2),'rs');
      I = I + 1;
    end
    %
    line([PTS1(1,1),PTS1(2,1)], [PTS1(1,2),PTS1(2,2)], 'LineStyle', '-','Color','b');
    line([PTS1(2,1),PTS1(3,1)], [PTS1(2,2),PTS1(3,2)], 'LineStyle', '-','Color','b');
    line([PTS1(3,1),PTS1(4,1)], [PTS1(3,2),PTS1(4,2)], 'LineStyle', '-','Color','b');
    hold off
    xlim([-1.2 0]); ylim([0 1.2]);
    title(sprintf('Elongation - Mode %d',M))
    %
    line([PTS(1,1),PTS(1,1)], [PTS(1,2),PTS(1,2)], 'LineStyle','--','Color','k');
    line([PTS(2,1),PTS(2,1)], [PTS(2,2),PTS(2,2)], 'LineStyle','--','Color','k');
    line([PTS(3,1),PTS(3,1)], [PTS(3,2),PTS(3,2)], 'LineStyle','--','Color','k');
    line([PTS(4,1),PTS(4,1)], [PTS(4,2),PTS(4,2)], 'LineStyle','--','Color','k');
  end
end
if FL(8) % Elongation modeshape time histories
    figure(8)
    for M = 1:MLen,
        Y = zeros(length(MovWin.PCA.Disp.EigVec),MLen);
        for I = 1:MLen
            for K = 1:length(MovWin.PCA.Disp.EigVec)
                Y(K,I) = MovWin.PCA.Disp.EigVec{K}(I,M);
            end
        end
        subplot(MLen,1,M)
        T = cell2mat(MovWin.PCA.Disp.Time.End.DateNum);
        T = reshape(T,MLen,length(MovWin.Time.DateNum)); T = T';
        plot(T,Y,'LineWidth',1.5)
        datetick('x','mm/dd'); xlabel('Time'); ylabel('Elongation'); grid on;
    end
end

if FL(9) % Tilt modeshape time histories
    figure(9)
    for M = 1:MLen,
        Y = zeros(length(MovWin.PCA.Tilt.EigVec),MLen);
        for I = 1:MLen
            for K = 1:length(MovWin.PCA.Tilt.EigVec)
                Y(K,I) = MovWin.PCA.Tilt.EigVec{K}(I,M);
            end
        end
        subplot(MLen,1,M)
        T = cell2mat(MovWin.PCA.Tilt.Time.End.DateNum);
        T = reshape(T,MLen,length(MovWin.Time.DateNum)); T = T';
        plot(T,Y,'LineWidth',1.5)
        datetick('x','mm/dd'); xlabel('Time'); ylabel('Tilt'); grid on;
    end
end

if FL(10) %
    Mat = cell2mat(MovWin.PCA.Tilt.EigVec);
    Mat = reshape(Mat,MLen,MLen,length(MovWin.PCA.Tilt.EigVec));
    Node1 = Mat(1,1,:); Node1 = squeeze(Node1);
    Node2 = Mat(2,1,:); Node2 = squeeze(Node2);
    Node3 = Mat(3,1,:); Node3 = squeeze(Node3);
    Node4 = Mat(4,1,:); Node4 = squeeze(Node4);
    %
    Mat = cell2mat(MovWin.PCA.Tilt.EigVal);
    Wt1 = Mat(1,:); Wt1 = Wt1';
    Wt2 = Mat(2,:); Wt2 = Wt2';
    Wt3 = Mat(3,:); Wt3 = Wt3';
    Wt4 = Mat(4,:); Wt4 = Wt4';
    %
    Node1 = Wt1.*Node1./Node1(1); % Bottom sensor
    Node2 = Wt1.*Node2./Node2(1);
    Node3 = Wt1.*Node3./Node3(1);
    Node4 = Wt1.*Node4./Node4(1); % Top sensor
    Node = [Node1 Node2 Node3 Node4];
    %
    T = cell2mat(MovWin.PCA.Tilt.Time.End.DateNum);
T = reshape(T, MLen, length(MovWin.Time.DateNum)); T = T';
plot(T, Node, 'LineWidth', 1.5)
datetick('x', 'mm/dd'); xlabel('Time'); ylabel('Tilt'); grid on;
legend({'Node 1', 'Node 2', 'Node 3', 'Node 4'})
end

%---
if FL(11)
    Mat = cell2mat(MovWin.PCA.Disp.EigVec);
    Mat = reshape(Mat, MLen, MLen, length(MovWin.PCA.Disp.EigVec));
    Node1 = Mat(1, 1, :); Node1 = squeeze(Node1);
    Node2 = Mat(2, 1, :); Node2 = squeeze(Node2);
    Node3 = Mat(3, 1, :); Node3 = squeeze(Node3);
    Node4 = Mat(4, 1, :); Node4 = squeeze(Node4);
    %
    Mat = cell2mat(MovWin.PCA.Disp.EigVal);
    Wt1 = Mat(1, :); Wt1 = Wt1';
    Wt2 = Mat(2, :); Wt2 = Wt2';
    Wt3 = Mat(3, :); Wt3 = Wt3';
    Wt4 = Mat(4, :); Wt4 = Wt4';
    %
    Node1 = Wt1.*Node1./Node1(1); % Bottom sensor
    Node2 = Wt1.*Node2./Node2(1);
    Node3 = Wt1.*Node3./Node3(1);
    Node4 = Wt1.*Node4./Node4(1); % Top sensor
    Node = [Node1 Node2 Node3 Node4];
    %
    T = cell2mat(MovWin.PCA.Disp.Time.End.DateNum);
    T = reshape(T, MLen, length(MovWin.Time.DateNum)); T = T';
    plot(T, Node, 'LineWidth', 1.5)
datetick('x', 'mm/dd'); xlabel('Time'); ylabel('Disp'); grid on;
legend({'Node 1', 'Node 2', 'Node 3', 'Node 4'})
end
REFERENCES


