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Deformation analysis in tunnels through curve clustering

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ABSTRACT

Deformations in tunnels and galleries due to confinement pressures can occur continuously but also at discrete time intervals. We propose a methodology to detect discrete significant deformations in tunnels based on a probabilistic model-based curve clustering. An EM (expectation-maximization) algorithm is used to obtain the parameters of the component density functions that maximize the log-likelihood function. The estimation of the number of clusters was performed by means of the Bayesian Information Criterion (BIC).

The proposed methodology was applied to the analysis of the deformations in a tunnel that has been used in the past to transport coal in an underground mine. A set of 40 profiles measured over a period of 20 months were compared. The results obtained show that deformations are not continuous but significantly high deformation episodes occur.

1. Introduction

Monitoring of deformations in tunnels and galleries is indispensable to ensure their function and to prevent collapse. Deformation in tunnels occurs as a result of the redistribution of stresses around the excavation. The magnitude of the deformations depends on several factors such as the method of excavation, the rock mass conditions, the orientation of the excavation or the type of support used [1,2].

Monitoring deformation of tunnels is useful for construction and maintenance practices. There are different methods to measure deformations in tunnels, such as tape extensometers, geodetic surveys (using total stations or levels), close-range photogrammetry or terrestrial laser scanning (TLS). Sometimes it is necessary to use a combination of techniques to ensure reliable results.

Tape extensometers are the most accurate of the devices listed. They have an accuracy of approximately ±0.2 mm over 10–15 m [3,4]. The main limitation is that the tape extensometers are only able to control deformation between anchor points sited on the surface of the tunnel. The anchor points must be installed in the construction process when it is safe to access the excavation and the support has been installed.

The total station determines the position (x, y, z) of some points (usually 5–7 points) on the surface of the tunnel. Total station can use reflectors installed around the profile of the tunnel or use the laser distance measurement that does not require reflectors. It is necessary to have stable points outside the zone of deformation in order to determine the displacements produced. Nowadays, deformation monitoring with total station can be achieved via manual observations or with automatic total stations,

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which are permanently fixed on the structure. Tunnel monitoring needs a first order total station, a typical total station for this kind of works has an accuracy of about ±1 mm [3,5].

Photogrammetric techniques require a series of reference points distributed on the surface of the tunnel, which are photographed from at least two points to obtain a 3D model. Lighting is always a problem for photogrammetry and in a tunnel it is even more so. The accuracy of photogrammetric techniques is about ±2.5 mm [6,7]

TLS is a laser scanning technology that enables rapid and reasonably accurate representation, in the form of a point cloud, of the 3D surface of an object. Its use in underground excavations has greatly increased in recent years, given its capacity to scan large sections of tunnel rapidly and provide a 3D model of the excavated geometry [8,9]. The main advantage of using TLS rather than traditional surveying methods is that information can be obtained on the geometry of the tunnel along its entire length rather than on specific sections, usually at intervals of several meters; hence, any of the sections of a tunnel can be modeled and represented for study purposes. However, accuracy is lower than with the other techniques previously mentioned (around ±5 mm). Using TLS to measure tunnel geometry needs to be planned carefully to ensure accurate, reliable and cost-effective results [10,11].

A common practice to determine the deformation of a tunnel is to compare profiles measured at different times [12–14]. In tunnel monitoring the measured profiles are always compared to a reference profile. This profile is used to calculate the variation of the profile shape and magnitude of the deformation over time. Profile comparison usually consists in evaluating the differences between the coordinates of a set of points in the profiles, although the tunnel surface is continuous. Furthermore, sometimes differences between profiles are due to measurement errors, and this can lead to incorrect conclusions when a deformation analysis is performed. For that reason we propose to apply statistical methods to study deformations in tunnels and galleries. Measurement errors can be blunders, systematic or random. All of them affect profile comparison, although the statistical analysis performed in this paper is constrained to random errors as it is considered that blunders and systematic errors have been removed. In this line, Ordoñez et al. [15] carried out a comparison of tunnel profiles by means of the determination of functional outliers in order to evaluate the quality of the tunnel geometry. We are also interested in determining whether the deformation is continuous over time or, conversely, if some isolated episodes of major deformations occur. We consider that profile clustering can help to detect significant changes in the deformation process.

2. Methodology

2.1. Curve clustering model

The aim of this paper is to detect significant differences between profiles that give us information about deformations in tunnels or galleries. To this end, a mixture clustering model, also referred to as a model-based probabilistic clustering [16] is proposed. In mixture models [17], the data, that come from some population of interest, are supposed to have been generated by a finite mixture model with K components, being K the number of clusters.

A particular advantage of the probabilistic versus the deterministic approach (e.g. k means clustering) is that the components PDFs can be defined on non-vector data. In a curve clustering context, being $\mathbf{Y} = \{\mathbf{y}_1, \ldots, \mathbf{y}_n\}$, a sequence of curves observed at n_i points $\mathbf{x}_i$, it is possible to define a cluster conditional probabilistic model that relates $\mathbf{y}_i$ to $\mathbf{x}_i$ according to the following expression:

$$p(\mathbf{y}_i|\mathbf{x}_i, \Theta) = \sum_{k=1}^{K} \alpha_k p_k(y_i|\mathbf{x}_i, \theta_k) \tag{1}$$

where $p_k(\cdot)$ represents component density functions associated with each cluster, $p(\cdot)$ the component density function associated to $\mathbf{y}_i$ α_k non-negative mixture weights that sum one and $\boldsymbol{\theta}_k$ the parameters characterizing each density function (i.e. mean and standard deviation for Gaussian distributions) [18].

Conditional probability density functions are derived from a pth order polynomial regression model with an additive Gaussian error term:

$$\mathbf{y}_i = \mathbf{X}_i\beta + \varepsilon_i, \qquad \varepsilon_i \sim \mathcal{N}\left(\mathbf{0}, \sigma^2\mathbf{I}\right) \tag{2}$$

where $\mathbf{X}_i$ represents the $n_i \times (p+1)$ Vandermonde regression matrix and $\boldsymbol{\beta}$ the (p + 1)-vector of regression coefficients. By considering the data as curves instead of vectors we can leverage the smoothness information contained in the sequence of data that is not explicit in vector form. Other smoothing methods, such as splines, can also be used to approximate the data [18].

Taking into account (2), density components are Gaussian, and then Eq. (1) can be rewritten as follows:

$$p(\mathbf{y}_i|\mathbf{X}_i, \Theta) = \sum_{k=1}^{K} \alpha_k \mathcal{N}\left(\mathbf{y}_i|\mathbf{X}_i\beta_k, \sigma_k^2\mathbf{I}\right). \tag{3}$$

The clustering problem reduces to maximizing the log-likelihood function

$$\mathcal{L}(\Theta|\mathbf{y}_1, .., \mathbf{y}_n) = \log\prod_{i=1}^{n} p(\mathbf{y}_i|\mathbf{X}_i, \Theta) = \sum_{i=1}^{n}\log\sum_{k=1}^{K} \alpha_k \mathcal{N}\left(\mathbf{y}_i|\mathbf{X}_i\beta_k, \sigma_k^2\mathbf{I}\right) \tag{4}$$