Procedia Computer Science
Volume 80, 2016, Pages 577–586
ICCS 2016. The International Conference on Computational Science

Crack Detection in Earth Dam and Levee Passive Seismic Data Using Support Vector Machines

Wendy D. Fisher[1], Tracy K. Camp[1], and Valeria V. Krzhizhanovskaya[2,3,4]

[1] Colorado School of Mines, Golden, Colorado, U.S.A.
wbelcher@mines.edu, tcamp@mines.edu
[2] University of Amsterdam, Science Park 904, 1098 XH, Amsterdam, the Netherlands
V.Krzhizhanovskaya@uva.nl
[3] National Research University ITMO, St. Petersburg, 197101, Russia
[4] St. Petersburg State Polytechnic University, St. Petersburg, 195251, Russia

Abstract

We investigate techniques for earth dam and levee health monitoring and automatic detection of anomalous events in passive seismic data. We have developed a novel data-driven workflow that uses machine learning and geophysical data collected from sensors located on the surface of the levee to identify internal erosion events. In this paper, we describe our research experiments with binary and one-class Support Vector Machines (SVMs). We used experimental data from a laboratory earth embankment (80% normal and 20% anomalies) and extracted nine spectral features from decomposed segments of the time series data. The two-class SVM with 10-fold cross validation achieved over 97% accuracy. Experiments with the one-class SVM use the top two features selected by the ReliefF algorithm and our results show that we can successfully separate normal from anomalous data observations with over 83% accuracy.

Keywords: Data-driven levee monitoring, machine learning, anomaly detection, passive seismic.

1 Introduction

In this paper, we describe our research for the advancement of earth levee health assessment. We are developing a novel data-driven workflow for the automatic detection of anomalous events that uses machine learning and geophysical data to identify internal erosion events. Our lightweight anomaly detection scheme builds upon our work using unsupervised clustering [1], which shows a clear separation of events (e.g., cracks) from non-events. We begin by discussing the background and motivation for our application to earth levee passive seismic data.

1.1 Identifying Internal Erosion Events in Earth Dams and Levees

Earth dams and levees are constructed with earthen materials such as rock, sand, and clay [2] and are built primarily for flood control, water storage, and irrigation. The main causes of earth

Selection and peer-review under responsibility of the Scientific Programme Committee of ICCS 2016

doi:10.1016/j.procs.2016.05.339

levee failures are typically due to piping, slope instability, foundation issues, or overtopping [3]. Figure 1 shows the result of internal erosion and piping that caused a dam failure and view of a downstream town that had to be evacuated. Since many U.S. earth dams are nearing the end of their design life (i.e., over 60 years old) [4] and facing the increasing frequency and severity of storms around the globe, it is important to find ways to efficiently monitor earth levee stability. We research the use of machine learning methods and geophysical sensor technologies to identify potential problems and better understand the structural integrity of earth levees.

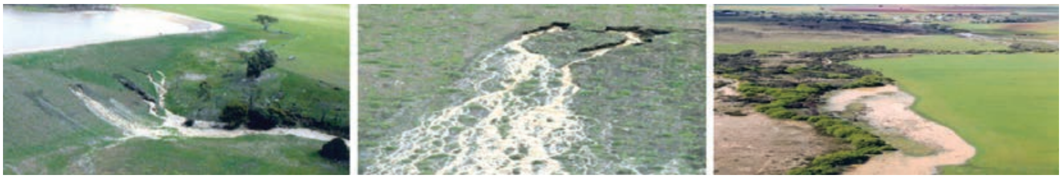

Figure 1: Tunbridge Dam in Tasmania, Australia that experienced failure by internal erosion (piping) and view of evacuated town downstream (Source: Jeffery Farrar (2008) [5])

Researchers at the University of Amsterdam detected anomalies in earth levees from sensors installed inside the dams (e.g., temperature, pore water pressure, relative inclination) using a one-sided classification approach [6]. In other words, they detected deviations from what is considered a normal state of the dam or levee. Researchers at Mississippi State University experimented with unsupervised and supervised methods to detect anomalies [7] and classify levee slides [8] [9] along the Mississippi River. They investigated the use of a support vector machine to identify anomalous activity in synthetic aperture radar data. Our novel approach investigates detecting internal erosion events that could lead to failure by using geophysical data collected from sensors located on the surface of the levee, thereby retaining the integrity of the structure.

1.2 Detection of Anomalies

Machine learning is a branch of artificial intelligence where a computer can learn from data without human assistance. Anomaly detection is used to identify data observations that deviate from the normal or expected pattern. The detection of an anomaly in a dataset is important since an anomaly can indicate a potentially serious issue. The broad categories of anomaly detection found in the literature [10] are: supervised, semi-supervised, and unsupervised. The supervised approach requires the use of labeled training data for both normal and anomalies. This approach is often a good first step in experimentation; however, this approach is typically not the preferred method since the availability of labeled anomalous data is often unavailable or is difficult to obtain for every possible occurrence. A semi-supervised technique only requires labeled training data for what is considered normal, which is more readily available. Once a model is trained, anomalies are identified through testing the likelihood of membership. Unsupervised anomaly detection does not use labeled training data, assumes the majority class is normal, and defines outliers as anomalies in the data set. The unsupervised approach is usually the most appropriate technique for many anomaly detection problems.

The development of an anomaly detection scheme is needed in our domain of interest due to the large class imbalance of data; in other words, there is a lack of anomalous observational data in our datasets. With this approach, we can train models with what is considered normal data and detect deviations within a certain threshold. We experiment with the supervised (i.e.,