Poster Abstract: Sensor Networks for Landslide Detection

Andreas Terzis
Johns Hopkins University
Computer Science Department
terzis@cs.jhu.edu

Kevin Moore
Colorado School of Mines
Division of Engineering
kmoore@mines.edu

Annalingam Anandarajah
Johns Hopkins University
Civil Engineering Department
rajah@jhu.edu

I-Jeng Wang
Johns Hopkins University
Applied Physics Lab
I-Jeng.Wang@jhuapl.edu

ABSTRACT

In this paper we outline a sensor network for landslide detection. Network sensors deployed on the surface and underground the hill under observation, use distributed signal processing techniques to self-localize and detect any changes in their relative locations. When such movements occur, changes in location as well as soil parameters are passed to a central location and used as input to a *Finite Element Model* that predicts whether and when a landslide will occur.

Categories and Subject Descriptors

C.2.4 [**Distributed Systems**]: Distributed Applications.

General Terms

Algorithms, Design, Measurement

Keywords

Landslide Detection, Sensor Networks, Belief Propagation, Localization

1. INTRODUCTION

Landslides are geological phenomena affecting people around the globe, causing significant loss of life and billions of dollars in damages each year. Although a basic understanding of the causes and behavior of landslides is available, systems that predict, detect, and warn people about the impending occurrence of a landslide at a specific site do not exist. This is due to two main reasons: First, though the root causes of landslides are known, much of this knowledge is qualitative and based on static measures. However, development of a landslide is a temporal process, which can take as long as a year or more. The quantitative, temporal indicators of this process and its progress are not fully understood. Second, the phenomenology of landslides is fundamentally spatial in nature. Though single point-location measurements of soil properties can be helpful, to effectively infer the potential for a landslide in a given location, it is important to be able to characterize soil properties over a suitably-sized region.

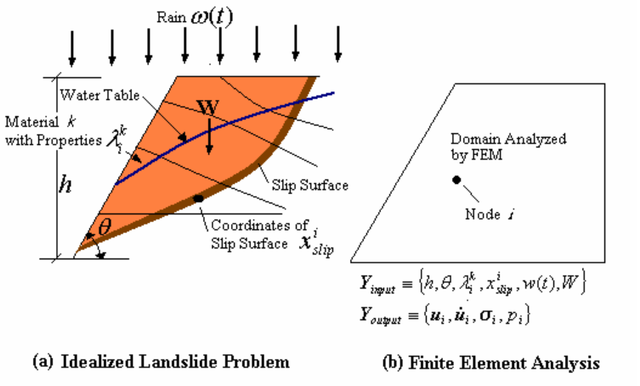
Our approach is to exploit wireless sensor network (WSN) technology to develop a spatial-temporal sensor system that can be used for (1) improving scientific understanding of landslide phenomena and (2) real-time monitoring and assessment of sites with high landslide risk. The network of wireless sensors will collect and collaboratively process measurements from the field before forwarding them to an analysis station. The analysis station will execute more computationally-intensive algorithms (such as finite element modeling and parameter identification) and will act as the operator interface to the system. The operator will be able to retask the system through the analysis section by changing the frequency and the spatial granularity at which measurements are taken.

2. LANDSLIDE DETECTION

We use the finite element method [1] (FEM in short) to predict the onset of a landslide. The parameters shown in Figure 1.(a) are FEM input parameters, which are grouped in a vector as $\boldsymbol{Y}_{input} \equiv \{h, \theta, \lambda_i^k, \omega(t), W\}$. Given $\boldsymbol{Y}_{input}$, FEM calculates the time history of displacements ($\boldsymbol{u}_i(t)$), velocities($\dot{\boldsymbol{u}}_i(t)$), stresses ($\mathbf{s}_i$), and pore water pressures (p_i) at any point i in the slope. We group these output variables in a vector as $\boldsymbol{Y}_{output} \equiv \{\boldsymbol{u}_i, \dot{\boldsymbol{u}}_i, \mathbf{s}_i, p_i\}$. The input and output parameters are shown in Figure 1.(b). Among the input parameters, the slope height h, the slope angle θ, and the rate of water inflow $\omega(t)$ can be directly measured and treated as known parameters. The location of the slip surface x_{slip}^i will be estimated through distributed signal processing based on distributed sensor measurements. We refer to the remaining input parameters as unknown parameters for FEM analysis and denote them by $\boldsymbol{Y}_{input}^{unknown}$.

FEM calculates $\boldsymbol{Y}_{output}$ at any point i, however, the sensors are placed only at a subset of locations. Let $\boldsymbol{Y}_{output}^k$ be the FEM output at the nodes where sensors are placed, $\boldsymbol{S}^k$ be the corresponding sensor readings. In an ideal case where $\boldsymbol{Y}_{input}^{unknown}$ is known and FEM represents the mechanical behavior perfectly, $\boldsymbol{Y}_{output}^k = \boldsymbol{S}^k$. Hence an optimal value for $\boldsymbol{Y}_{input}^{unknown}$ can be obtained by minimizing a scalar objective function defined in terms of the difference between $\boldsymbol{Y}_{output}^k$ and $\boldsymbol{S}^k$. This inverse analysis of system identification begins with a trial set for $\boldsymbol{Y}_{input}^{unknown}$ and computes an optimal set for $\boldsymbol{Y}_{input}^{unknown}$ by a suitable nonlinear optimization method. As the sensor data is gathered continuously, the procedure will be repeated at suitable time intervals, and $\boldsymbol{Y}_{input}^{optimal}$ updated.

SenSys'05, November 2–4, 2005, San Diego, California, USA.
ACM 1-59593-054-X/05/0011.



(a) Idealized Landslide Problem (b) Finite Element Analysis

Figure 1. Schematic of Landslide Problem and Domain Used for Finite Element Analysis.

3. SENSOR NETWORK

The wireless sensor network shown in Figure 2 collects the variables required by the finite element model described in the previous section. Specifically, the sensors in the network estimate the temporal displacements $\boldsymbol{u}_i(t)$ as well as the soil's water content and pore water pressures at different locations in the field. Temporal displacements are calculated through a tri-lateration technique using seismic sources on the hill surface and geophones connected to the sensor nodes. The nodes in the sensor network collaborate through the distributed signal processing algorithms described in the following section to detect the location of the *slip surface,* which is the surface separating the static part of the hill from the moving part. Note that until the existence of a slip plane is confirmed, no measurements are sent back to the analysis station, to reduce the amount of data transmitted and thus minimize energy consumption. After the existence and the location of a slip plane have been identified, ground parameters from sensors above the slip surface are passed back to the analysis station.

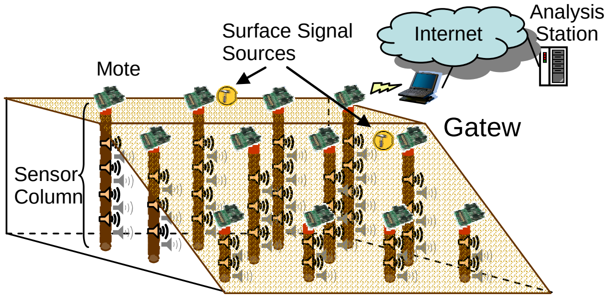


Figure 2. Landslide Wireless Sensor Network..

4. DISTRIBUTED SIGNAL PROCESSING

Before the hill movement we assume that we have established baseline distances between each pair of seismic source *i* and geophone *j*, denoted as $S_{ij}(t)$. We further assume that the initial locations of all the sensors are known (we denote these as $q_i(t)$). In the event of a hill movement some of these distances will change, denoted by $S_{ij}(t+\Delta)$. The goal of the distributed signal processing algorithm is to determine the approximate location of the slip surface as well as the new locations of the sensors, $q_i(t+\Delta)$, from which the displacements $u_i(t+\Delta)$ can be found.

The outline of our algorithm is as follows: **(1)** Given the available $S_{ij}(t)$ and $S_{ij}(t+\Delta)$, we apply *Belief Propagation* [2] or related messaging passing algorithms to classify the set of nodes into two sets: ones that moved and ones that stayed fixed. Intuitively, the first set contains nodes that lie *above* the slip surface while the second contains the nodes that lie *below* the slip surface. This is a non-trivial task, because in three dimensions, it is possible that several different node movement events could lead to the same change in distance. However, exploiting the known *a priori* relationships between the nodes a unique solution or a solution with high confidence can be found. Belief propagation and its variants provide a natural, Bayesian-theoretic mechanism for combining a priori information with sensor measurements. **(2)** Given these two sets, we can approximate the slip surface, x^i_{slip}, by finding a surface that separates the two sets with the largest margin or smallest possible error when the two sets are not separable. **(3)** Finally, given $S_{ij}(t)$, $S_{ij}(t+\Delta)$, and $q_i(t)$, tri-lateralization techniques can be used to find $q_i(t+\Delta)$, from which $u_i(t+\Delta) = q_i(t+\Delta) - q_i(t)$ can be computed. The updated sensor locations are fed to the FEM that uses them to predict future hill movements.

5. REFERENCES

[1] Zienkiewicz, O.C. and Taylor, R.L. *The finite element method.* Vol I, 4th Edition, MacGraw-Hill, 1989.

[2] Pearl, J. Probabilistic Reasoning in Intelligent Systems. Morgan Caufman, San Mateo, CA, 1998.