Volcanic Earthquake Timing Using Wireless Sensor Networks

Guojin Liu¹,²   Rui Tan²,³   Ruogu Zhou²   Guoliang Xing²   Wen-Zhan Song⁴   Jonathan M. Lees⁵

¹Chongqing University, P.R. China
²Michigan State University, USA
³Advanced Digital Science Center, Illinois at Singapore
⁴Georgia State University, USA
⁵University of North Carolina at Chapel Hill, USA
Volcano Hazards

- 7% world population live near active volcanoes
- 20 - 30 explosive eruptions/year
Volcano Monitoring

• Seismic activity monitoring
  – Earthquake localization, tomography, early warning etc.

• Traditional seismometer
  – Expensive (~$10K/unit), difficult to install & retrieve
  – Only ~10 nodes installed for most threatening volcanoes!

Sensor Networks for Volcano Monitoring

- Sensor systems for volcano monitoring
  - Harvard, OASIS@GSU, VolcanoSRI@GSU/MSU/UNC
  - Raw data collection@100Hz & centralized analysis
  - Short lifetime (~1 week)

- In-network earthquake detection [Tan 2010]
  - Distributed seismic signal processing
  - 83% energy reduction from raw data collection
**Earthquake Timing**

- Key to localization, seismic tomography, etc.
  - Usually done manually, automation is expensive
Earthquake Timing

- Key to localization, seismic tomography, etc.
  - Usually done manually, automation is expensive

- *In-situ* P-phase picking w/ limited transmission
  - Data intensive
  - Sensors have limited compute & comm. capabilities
Seismic Signal: Sparsity

Original @ 100Hz

Time (second)
Seismic Signal: Sparsity

Original @ 100Hz
Sparsity=0.57

K-sparse signal:
\[ \frac{\| s - s_{(k)} \|_2}{\| s \|_2} < 5\% \]

\[ \text{sparsity} = \frac{k}{\text{signal length}} \]
Seismic Signal: Sparsity

Original @ 100Hz
Sparsity=0.57

Wavelet
Sparsity=0.14

K-sparse signal:
\[ \frac{\| s - s_{(k)} \|_2}{\| s \|_2} < 5\% \]

Sparsity = \[ \frac{k}{\text{signal length}} \]
Seismic Signal: Sparsity

Observation 1: wavelet sparsifies signal
Seismic Signal: Frequency-Time

4-level wavelet transform (length=1600)

thumbnail (length=100)

Low-pass band (0, 6.25Hz)

P-wave < 5Hz

Time (unit: 160ms)
Seismic Signal: Frequency-Time

4-level wavelet transform (length=1600)

thumbnail (length=100)

Low-pass band (0, 6.25Hz)
P-wave < 5Hz

Original (length=1600)
Seismic Signal: Frequency-Time

4-level wavelet transform (length=1600)

thumbnail (length=100)

original

Time (unit: 160ms)

Rough P-phase estimate

Original (length=1600)
Seismic Signal: Frequency-Time

4-level wavelet transform (length=1600)

Original (length=1600)

thumbnail (length=100)

Rough P-phase estimate

• Observation 2: P-phase estimate from thumbnail
Seismic Signal: Diversity

Node 1
sparsity=0.1

Node 10
sparsity=0.38

Earthquake 1
Seismic Signal: Diversity

Earthquake 1

Node 1
sparsity=0.1

Node 10
sparsity=0.38

Earthquake 2

Node 10
sparsity=0.14
Seismic Signal: Diversity

Observation 3: sensors have different sparsities
Outline

• Problem statement
• **Approach overview**
• Earthquake timing algorithms
• Performance evaluation
• Conclusion
Approach Overview

Cluster head
Approach Overview
• Lightweight signal processing algorithms
  – Signal sparsity
  – Preliminary P-phase from thumbnail
• Lightweight signal processing algorithms
  – Signal sparsity
  – Preliminary P-phase from thumbnail
Approach Overview

- Lightweight signal processing algorithms
  - Signal sparsity
  - Preliminary P-phase from thumbnail
- Select most informative sensors to TX
Approach Overview

- Lightweight signal processing algorithms
  - Signal sparsity
  - Preliminary P-phase from thumbnail
- Select most informative sensors to TX
  - Compressive sampling & transmission
Approach Overview

- Lightweight signal processing algorithms
  - Signal sparsity
  - Preliminary P-phase from thumbnail
- Select most informative sensors to TX
  - Compressive sampling & transmission

Source localization
Seismic tomography...
Outline

• Problem statement
• Approach overview
• Earthquake timing algorithms
  – Pre-processing @ sensors
  – Sensor selection & compressive sampling
• Performance evaluation
• Conclusion
Preliminary P-phase Pick

4-level wavelet transform (length=1600)

thumbnail (length=100)
Preliminary P-phase Pick

4-level wavelet transform (length=1600)

thumbnail (length=100)

\[
\text{preliminary pick} = 2^4 \times \arg \max_{p \in \text{thumbnail}} \frac{\text{signal energy after } p}{\text{signal energy before } p}
\]
Preliminary P-phase Pick

4-level wavelet transform (length=1600)

thumbnail (length=100)

Map thumbnail domain back to original time domain

preliminary pick = $2^4 \times \arg \max_{p \in \text{thumbnail}} \frac{\text{signal energy after } p}{\text{signal energy before } p}$
Preliminary P-phase Pick

4-level wavelet transform (length=1600)

thumbnail (length=100)

Map thumbnail domain back to original time domain

preliminary pick

$\text{preliminary pick} = \frac{2^4 \times \arg\max_{p \in \text{thumbnail}} \text{signal energy after } p}{\text{signal energy before } p}$

• Lightweight: $O(\text{signal length})$
  – Suitable for resource-constrained sensors
Outline

• Problem statement
• Approach overview

• Earthquake timing algorithms
  – Pre-processing @ sensors
  – Sensor selection & compressive sampling

• Performance evaluation
• Conclusion
Impact of Timing on Source Localization

• Source localization
  – Basis for many volcano monitoring applications
  – Complex non-linear inverse problem

\[ t_i = \text{ray tracing}(z_i, z_0, V) \]

• Information-theoretic error metric

\[ E = \text{tr}\left( (GG^T)^{-1} \right) \]

**scaled Fisher matrix:**

\[ G \]

\[ z_i, z_0 \]
Impact of Timing on Source Localization

• Source localization
  – Basis for many volcano monitoring applications
  – Complex non-linear inverse problem

\[ t_i = \text{ray tracing}(z_i, z_0, V) \]

• Information-theoretic error metric

\[ E = \text{tr} \left( (G G^T)^{-1} \right) \]

scaled Fisher matrix:
\[ z_i, z_0 \]
Impact of Timing on Source Localization

- Source localization
  - Basis for many volcano monitoring applications
  - Complex non-linear inverse problem

\[ t_i = \text{ray tracing}(z_i, z_0, V) \]

- Information-theoretic error metric

\[ E = \text{tr}\left( (GG^T)^{-1} \right) \]

scaled Fisher matrix:
- \( z_i, z_0 \)
Impact of Timing on Source Localization

- Source localization
  - Basis for many volcano monitoring applications
  - Complex non-linear inverse problem

\[ t_i = \text{ray tracing}(z_i, z_0, V) \]

- Information-theoretic error metric

\[ E = \text{tr}\left(\left(\mathbf{G}\mathbf{G}^T\right)^{-1}\right) \]

- scaled Fisher matrix:
  \[ z_i, z_0 \]
Dynamic Sensor Selection

• Find a subset of sensors $S$ to minimize $E$ s.t.

$$\sum_{i \in S} c_i \cdot m(\text{sparsity of sensor } i) \leq C$$
Dynamic Sensor Selection

• Find a subset of sensors $S$ to minimize $E$ s.t.

\[ \sum_{i \in S} c_i \cdot m(\text{sparsity of sensor } i) \leq C \]
Dynamic Sensor Selection

• Find a subset of sensors $S$ to minimize $E$ s.t.

$$\sum_{i \in S} c_i \cdot m(\text{sparsity of sensor } i) \leq C$$

unit TX cost

TX volume
Dynamic Sensor Selection

- Find a subset of sensors $S$ to minimize $E$ s.t.

$$\sum_{i \in S} c_i \cdot m(\text{sparsity of sensor } i) \leq C$$

- Unit TX cost
- TX volume
- Cost budget
Dynamic Sensor Selection

• Find a subset of sensors $S$ to minimize $E$ s.t.

$$\sum_{i \in S} c_i \cdot m(\text{sparsity of sensor } i) \leq C$$

• Brutal-force search
  – 8 seconds on Imote2 for 16 sensors
  – Information gain diminishes for larger clusters
Compressive Sampling (CS)

• Apply CS to wavelet coefficients
  – Known TX volume before compression
    \[ m = 1.5 \times \text{sparsity} \times n \]
  – Unselected sensors avoid compression overhead
Compressive Sampling (CS)

- Apply CS to wavelet coefficients
  - Known TX volume before compression
    \[ m = 1.5 \times \text{sparsity} \times n \]
  - Unselected sensors avoid compression overhead

Best trade-off b/w TX volume and signal reconstruction error
Outline

• Problem statement
• Approach overview
• Earthquake timing algorithms
• **Performance evaluation**
  – Testbed experiments
  – Extensive trace-driven simulations
• Conclusion
Testbed Experiments

• Implementation on 12 TelosB
  – Seismic data from Mt St Helens -> mote flash
  – Real-time data acquisition @ 100 Hz

![Bar chart showing execution time for different sensors](chart.png)

End-to-end delay < 3 seconds
Trace-driven Simulation

- Data traces from 12 sensors on Mt St Helens
- 30 significant earthquakes in 5.5 months

Configurable trade-off between system performance and energy consumption
Impact of Packet Loss

Lossy compression: encodes largest wavelet coefficients

CS is resilient to packet loss!
Impact of Packet Loss

Lossy compression: encodes largest wavelet coefficients

CS is resilient to packet loss!
Impact of Packet Loss

Lossy compression: encodes **largest** wavelet coefficients

CS is resilient to packet loss!
Accuracy of Timing

fine-grained pick on original

fine-grained pick on reconstructed
Accuracy of Timing

- Fine-grained pick on original
- Fine-grained pick on reconstructed

16% data TX
0.6 km localization error
Conclusions

• Energy-efficient earthquake timing
  – Lightweight algorithms for sensors
  – Dynamic sensor selection
  – Compressive sampling

• Testbed experiments
  – Feasibility of our approach on motes

• Trace-driven simulations
  – Accurate timing with 16% data transmitted
Hierarchical Network Architecture

- Sensors
  - Limited capability, large spatial coverage
- Coordinators
  - Powerful, limited number

500 nodes on Tungurahua, Ecuador, 2015 [VolcanoSRI project]

MCU & radio energy ratio TelosB vs. Imote2

STA/LTA detector
Bayesian detector
Earthquake Source Localization

Source localization result for an earthquake
16:56:47 Nov 03 2009 @ Mt St Helens
Earthquake Source Localization

Source localization result for an earthquake
16:56:47 Nov 03 2009 @ Mt St Helens

Localization error below 1km, common in volcano seismology
Only 16% data transmission