Wireless Sensor Network Technology for Avalanche Monitoring

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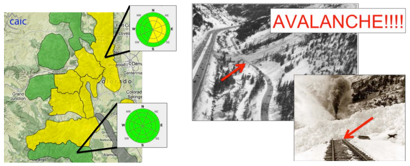
INTRODUCTION

• In Colorado, CDOT reports that 160 avalanche paths impact roads, causing nearly 1,000 hours of highway closures and over 6,000 hours of mitigation and cleanup efforts each year.

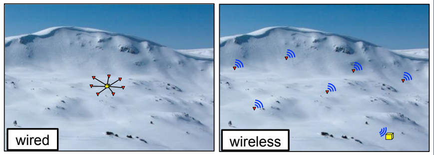
• My research focuses on using wireless sensor network technologies to monitor and automatically detect avalanches.

• Such technology could be used by forecasters to make better avalanche predictions or to notify transportation crews when to clean up avalanche debris.



WHY WIRELESS?

• Wireless sensor networks let scientists collect data with greater spatial diversity on the km scale.



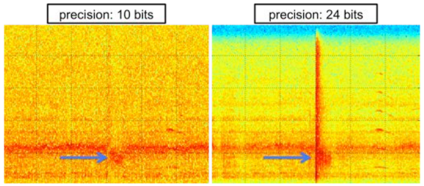
• With wireless sensors, there's no need to bury or maintain wires.

• **There are many research challenges associated with wireless geophysical monitoring…**

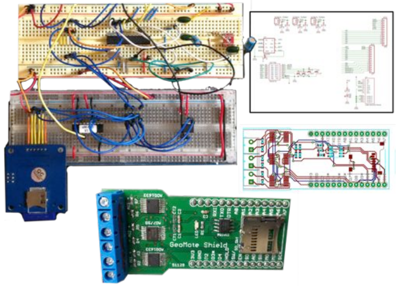
CUSTOM WIRELESS HARDWARE

• Off-the-shelf wireless devices (motes) lack the precision required for real-world geophysical monitoring.

• These wireless motes only have 10 to 12 bit analog to digital converters, which severely limits the amount of information geophysicists can derive from the collected data.



• To address this deficiency, we designed and implemented custom hardware that has a 24-bit analog to digital converter, 32 kB of SRAM, and an SD card socket.

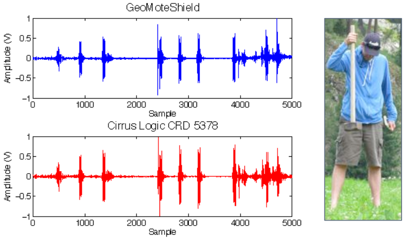


• Our custom hardware, called GeoMoteShield (GMS), is designed to plug into an off-the-shelf wireless mote (Arduino Fio).

• The GMS has an object-oriented API that allows non-computer scientists to easily program and control the board.

• We are currently testing the GMS against existing wired seismic and self potential data acquisition systems.

• Preliminary seismic test results show that our ~\$100 GMS performs comparably to an \$800 commercial (wired) system.



• We plan to conduct thorough geophysical experiments and quantitative analyses to compare the GMS to wired systems.

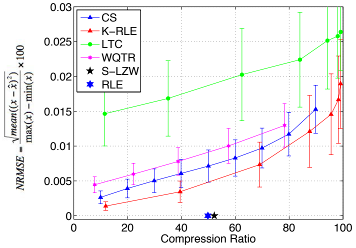
ON-MOTE COMPRESSION

• In wireless sensors, the radio consumes by far the most power.
   - Reducing the amount of transmitted data can significantly lower power consumption and system cost.

• Through simulation on seismic data, we compared compressive sampling (CS) to five on-mote compression algorithms.
   - CS replaces the traditional notion of "sample *then* compress" with "**compress *while* sampling**".
   - CS is ***non-adaptive***, meaning that the compression rate does not directly depend on signal redundancies.
      - Instead, compression is achieved by multiplying the signal with a randomized measurement matrix.
      - Decompression bears the computational burden; the original signal is estimated by solving the above transformation with assumed signal sparsity.

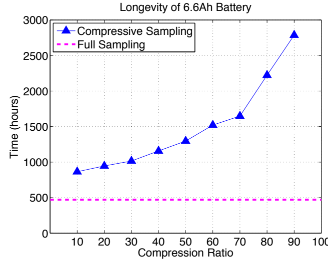
• In addition to CS, we evaluated three lossy algorithms: K-Run-Length Encoding (**K-RLE**) Lightweight Temporal Compression (**LTC**), and Wavelet Quantization Thresholding with RLE (**WQTR**),
   - and two lossless algorithms: Lempel-Ziv-Welch for Sensor Nodes (**S-LZW**) and Run-Length Encoding (**RLE**).

• After simulating compression, we calculated the normalized root mean square error (NRMSE) of the original vs. recovered signals.



• Our results show that CS was the second best performing lossy compression algorithm.
   - These results are striking, considering that CS is *non-adaptive*: the **compression rate is guaranteed**.
   - For the other five algorithms, the rate of compression is signal dependent and cannot be guaranteed.

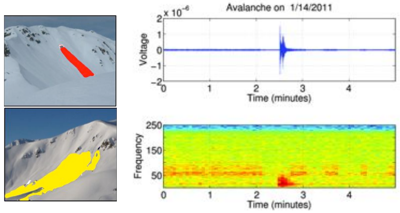
• We also implemented CS in hardware and did a power analysis.
   - CS significantly increased sensor node longevity.



AVALANCHE DETECTION

• During the 2010-2011 winter season, snow scientists recorded over 100 days of geophone data in the Swiss alps.

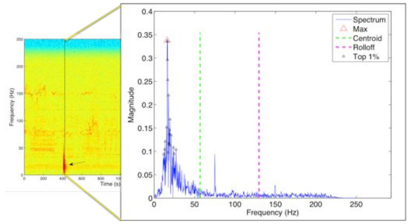
• The ***wired*** geophone array captured 33 large slab avalanches events and over 300 smaller sluffs.
   - The snow scientists wanted to use computers to automatically and reliably detect these events.



• In addition to avalanches, the seismic data was riddled with background noise caused by airplanes, helicopters, ski lifts, etc.

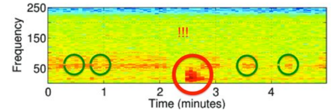
• We first used spectral flux based thresholding to select seismic events with instantaneous jumps in spectral energy.

• For each seismic event selected, we extracted many spectral features: e.g., centroid, spread, rolloff, mean top 1%, max, etc.



• We performed 100 iterations of training and testing using many different types of machine learning algorithms.
   - Since avalanches were very infrequent (about 0.2% of the total data), we used cluster based subsampling to better pick the non-avalanche events used for training.
   - Testing was performed on all data not used for training.

• Our results show that we can detect avalanches with 93% mean accuracy using a support vector machine classifier.



NEXT STEPS

- There are several next steps we plan to pursue.
   1. Implement the six on-mote compression algorithms in hardware and do a comparative power analysis. Will non-adaptive CS consume the least power?
   2. Apply this new technology to other domains: i.e., earth dam and levee monitoring.