TrailSense: A Crowdsensing System for Detecting Risky Mountain Trail Segments with Walking Pattern Analysis

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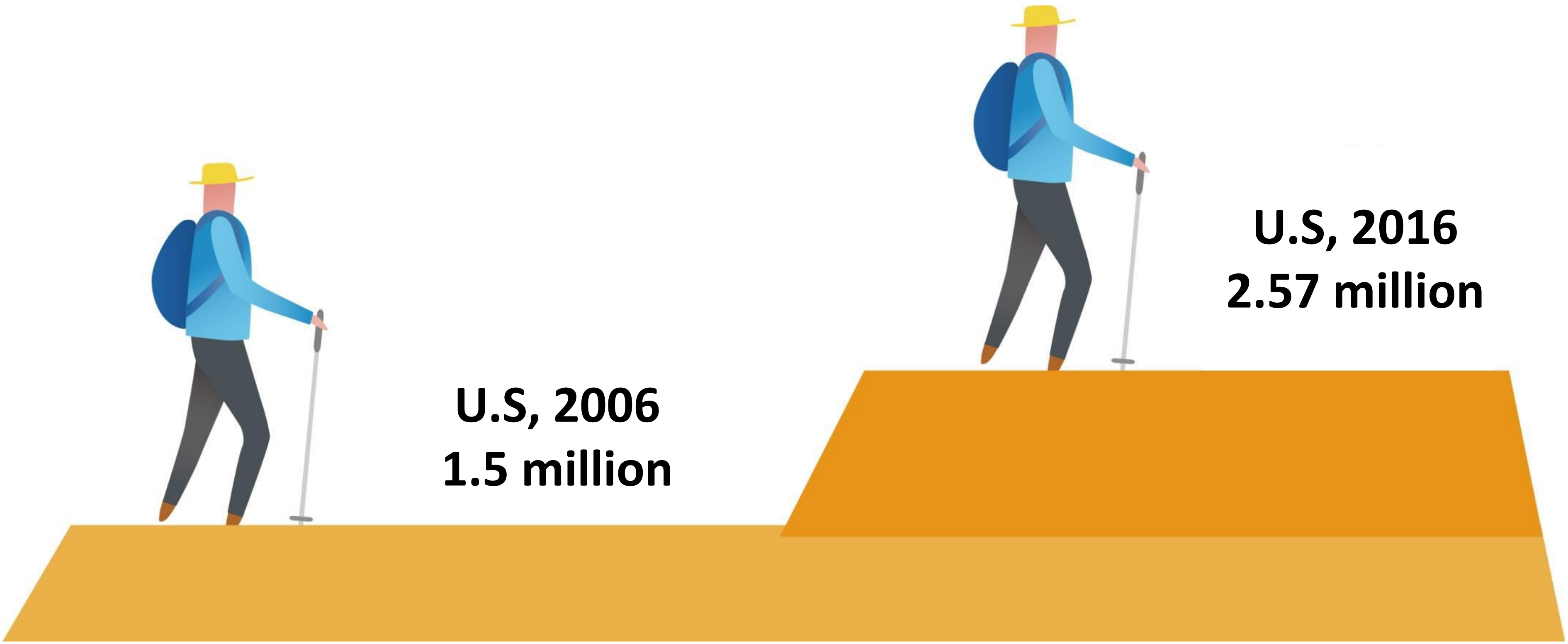
Motivation

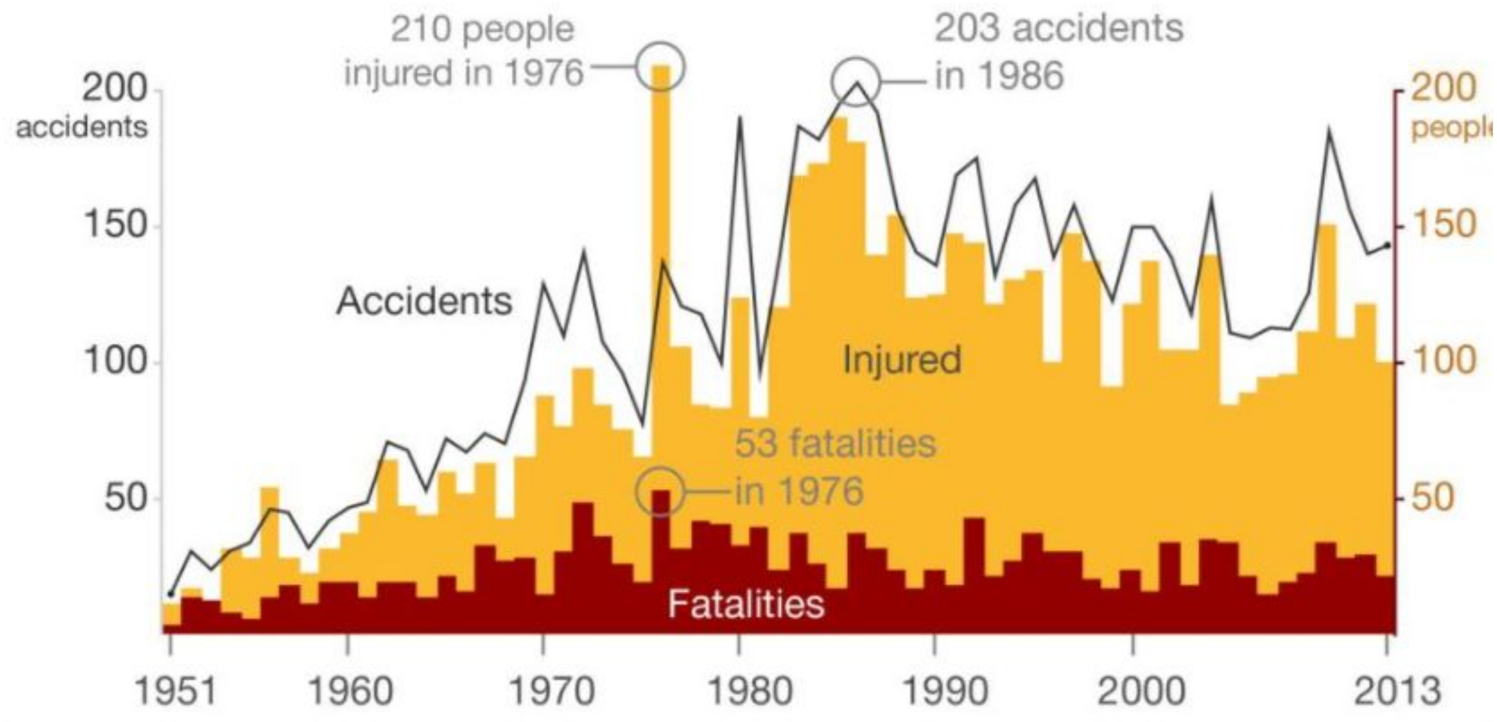
Mountain climbing is popular



[Outdoor Recreation Participation Topline Report 2016]

Motivation

Sometimes a mountaineering accident occurs in climbing

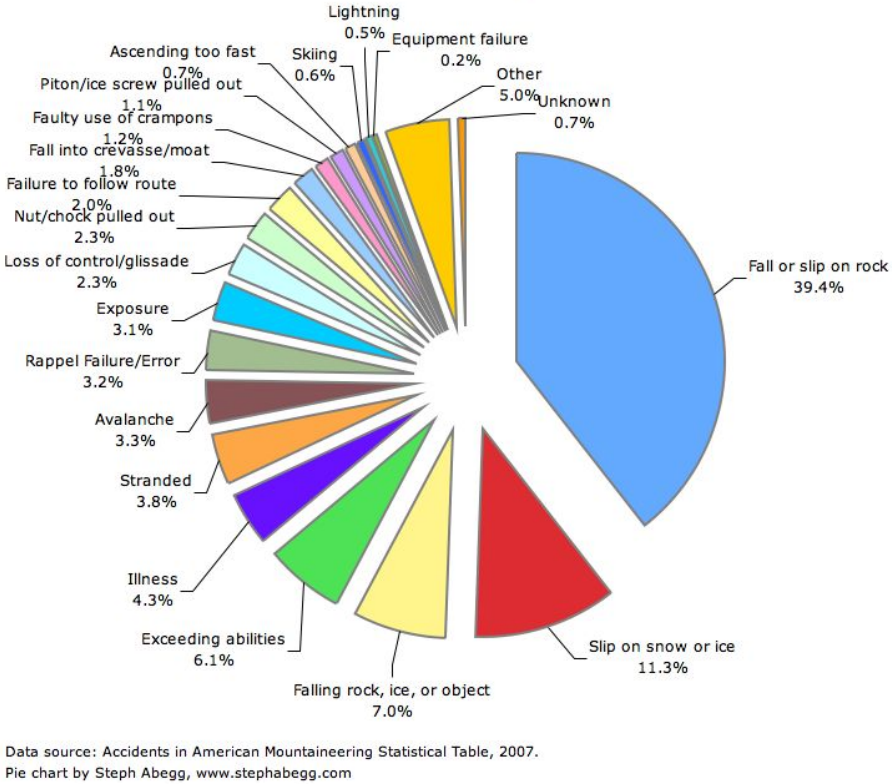


[American Alpine Club]

Motivation

Main cause of mountain accidents is ‘fall or slips on rock’

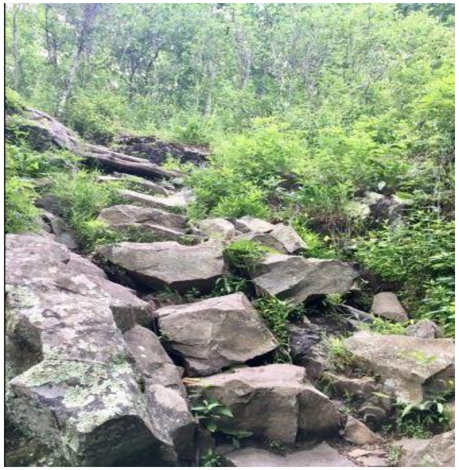
[US Mountaineering Accidents
By Immediate Cause 1951~2006]



Fall or Slip on rock : 39.4%

Motivation

Definition of Risky Trail



[Rocky Trail]

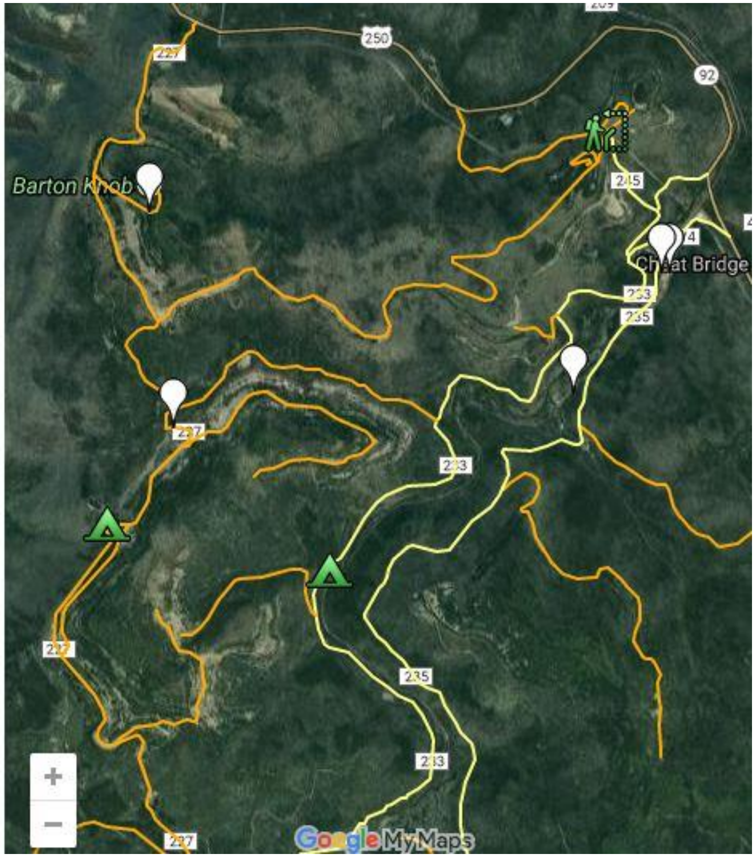
[More Fall and Slip]

'Risky Trail'

- Information on risky trails is needed for beginners

Motivation

Risky Mountain Trail Information on Google Map



[Google maps on mountain]

- Most used : Google Map
- Trail maps and trail length
- **No trail surface information**

Motivation

Collecting the Risky Trail Information

- Manual inspection method (send investigators to trail)
  - Cost limitation, Coverage limitation …
  - Not practical in real world

Concept of TrailSense

New automatic system for collecting trail surface information

Crowdsensing

- Motion Sensing – From climbers' smartphones
- Detect the risky trail segments by individual walking pattern
- Aggregate monitoring results to locate the risky trail segment

How TrailSense Classify Risky Trail Segments?

- Inferring trail surface via climbers' motion data

" Climbers show normal walking patterns in this trail…"

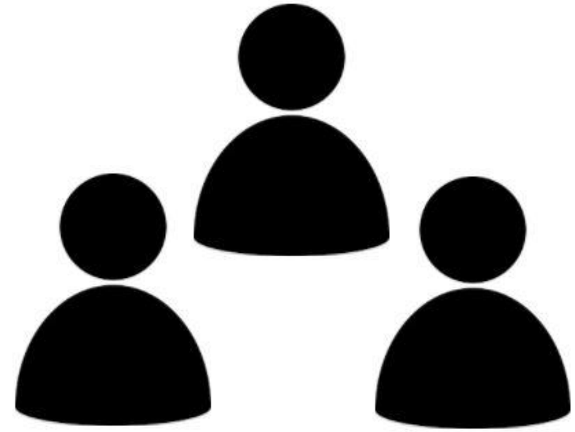
Then non-risky trail segment

" Climbers show abnormal behaviors…"

Then risky trail segment

- Algorithm 'learns' normal stride patterns of a climber and 'tells' whether current walking patterns are 'normal' or not

TrailSense Overview



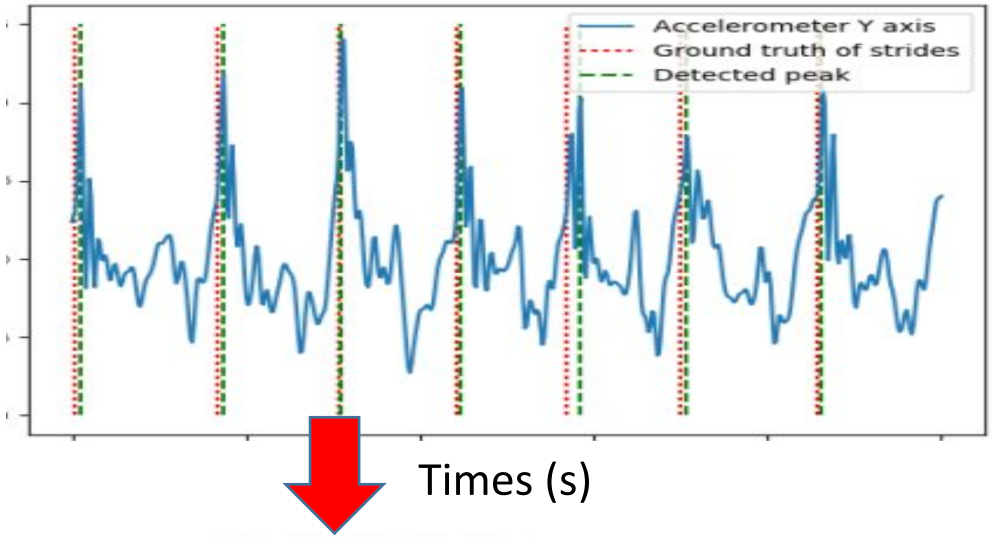
[Individual Sensing] **[Data aggregation]**

‘To learn the walking pattern and infer the riskiness’

Step 1	Step 2	Step 3	Step 4
Stride segmentation	Feature Extraction	Stride Classification	Windowing (Multiple strides)

- Stride Segmentation (Step 1)
  - Walking pattern analysis for learning normal stride pattern
  - Peak detection is used for Stride Segmentation

[Accelerometer Y axis]



Times (s)

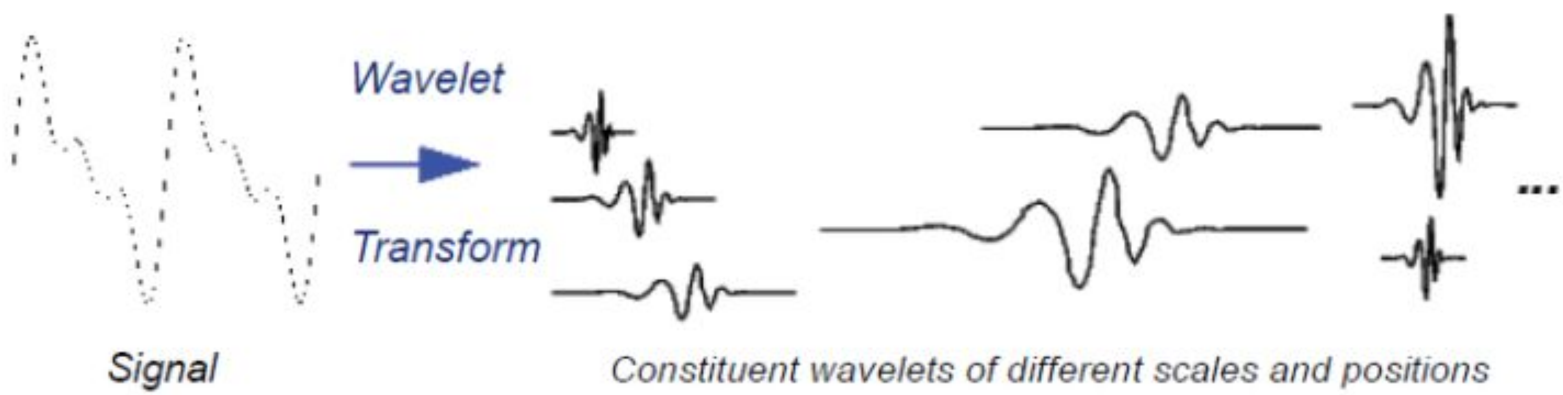
[Cyclic Walking pattern]

‘Peak on signal = Heel strike’

- Feature Extraction (Step 2)
  - Time domain features : absolute means, std, maximum
  - Time-frequency features : Discrete Wavelet analysis

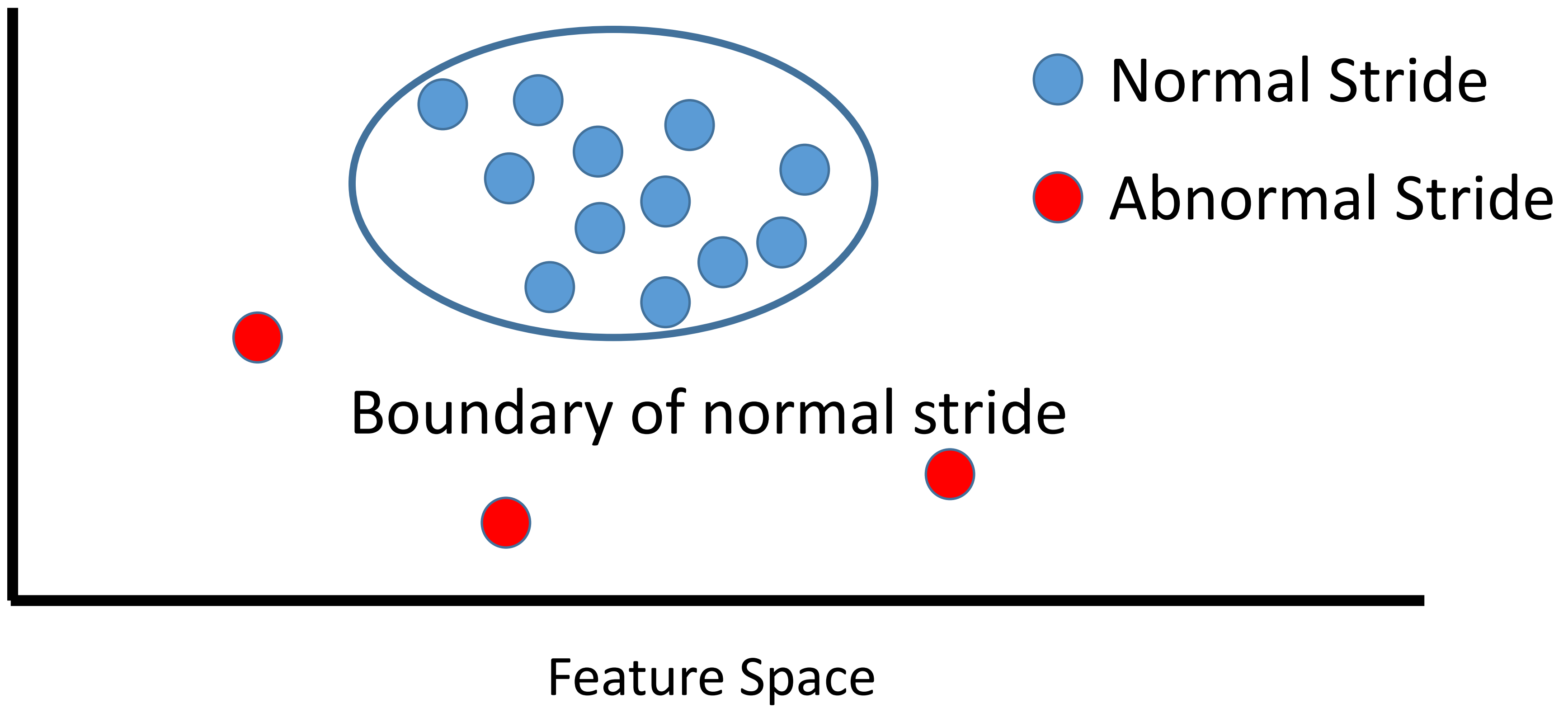
$$x(n) = \sum_{j=1}^{J} \sum_{k \in \mathbb{Z}} d_j(k)\psi\left(n - 2^j k\right) + \sum_{k\in\mathbb{Z}} a_J \phi(n - 2^j k)$$

- Wavelet can be applied in non-stationary signal (Time-Frequency)



- Stride Classification (Step 3)
  - One-Class SVM : Learns boundary of normal stride in feature space
  - One-class classification does not require data from risky segments

$$\max_{w,\rho,\xi} \rho - \frac{1}{\nu M}\sum \xi_i, \qquad s.t\ \left(w \cdot \Phi(X_i)\right) \geq \rho - \xi_i, \qquad \xi_i \geq 0$$



- Windowing for robust classification (Step 4)

" Climbers show normal walking patterns in this trail…"

Then non-risky trail segment

" Climbers show abnormal behaviors…"

Then risky trail segment

- Check window of multiple strides
- Check the relative ratio of abnormal strides

[Window 1] : Non-risky trail segment

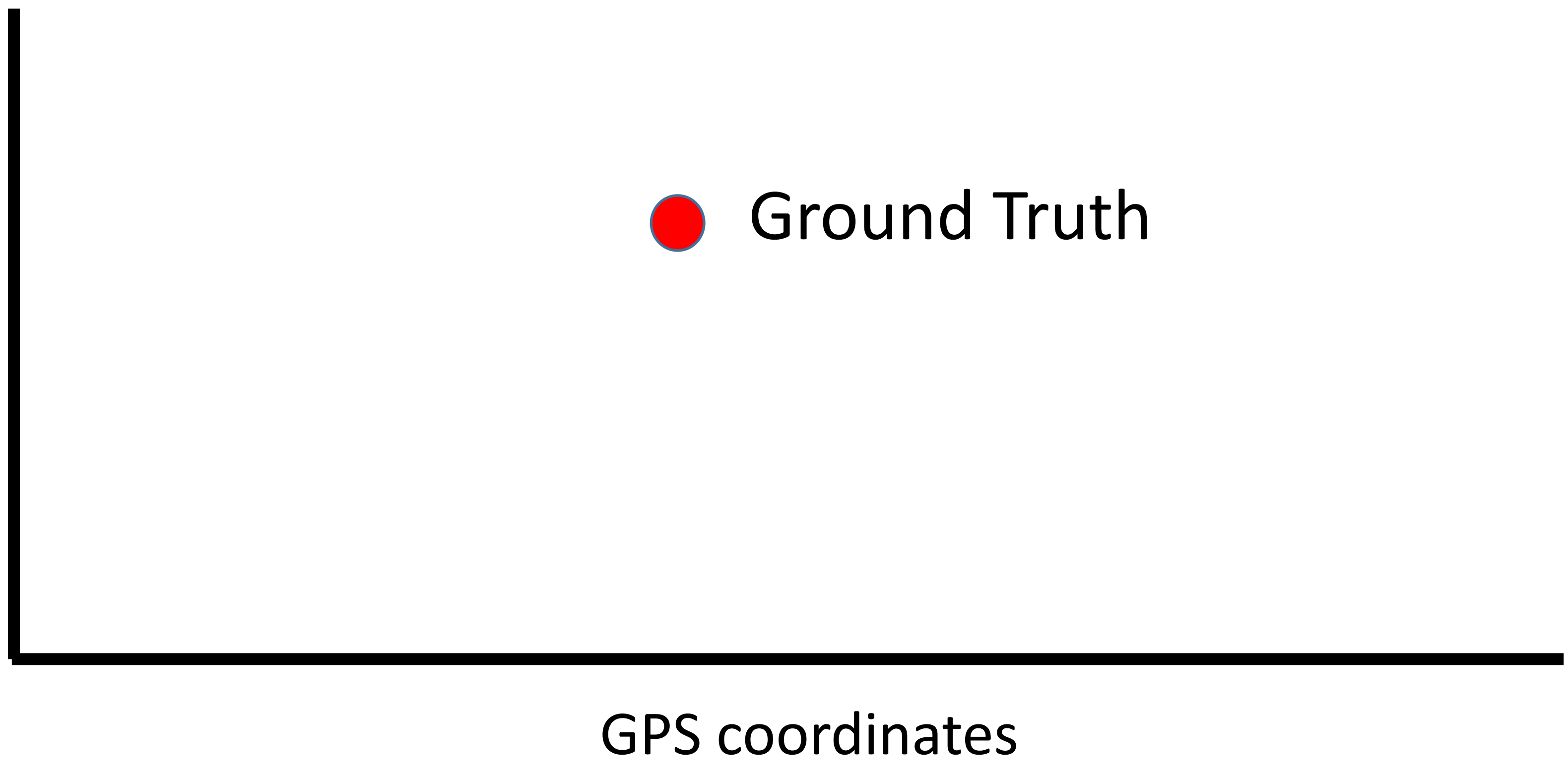
Normal	**Normal**	**Normal**	**Abnormal**	**Normal**

[Window 2] : Risky trail segment

Abnormal	**Normal**	**Abnormal**	**Abnormal**	**Abnormal**

Data Aggregation (After Individual Sensing)

- Aggregating results from the crowd
  - GPS data collected by a smartphone have a 10 meter margin of errors
  - False alarms can be generated
- Density based spatial clustering of applications with noise (DBSCAN)



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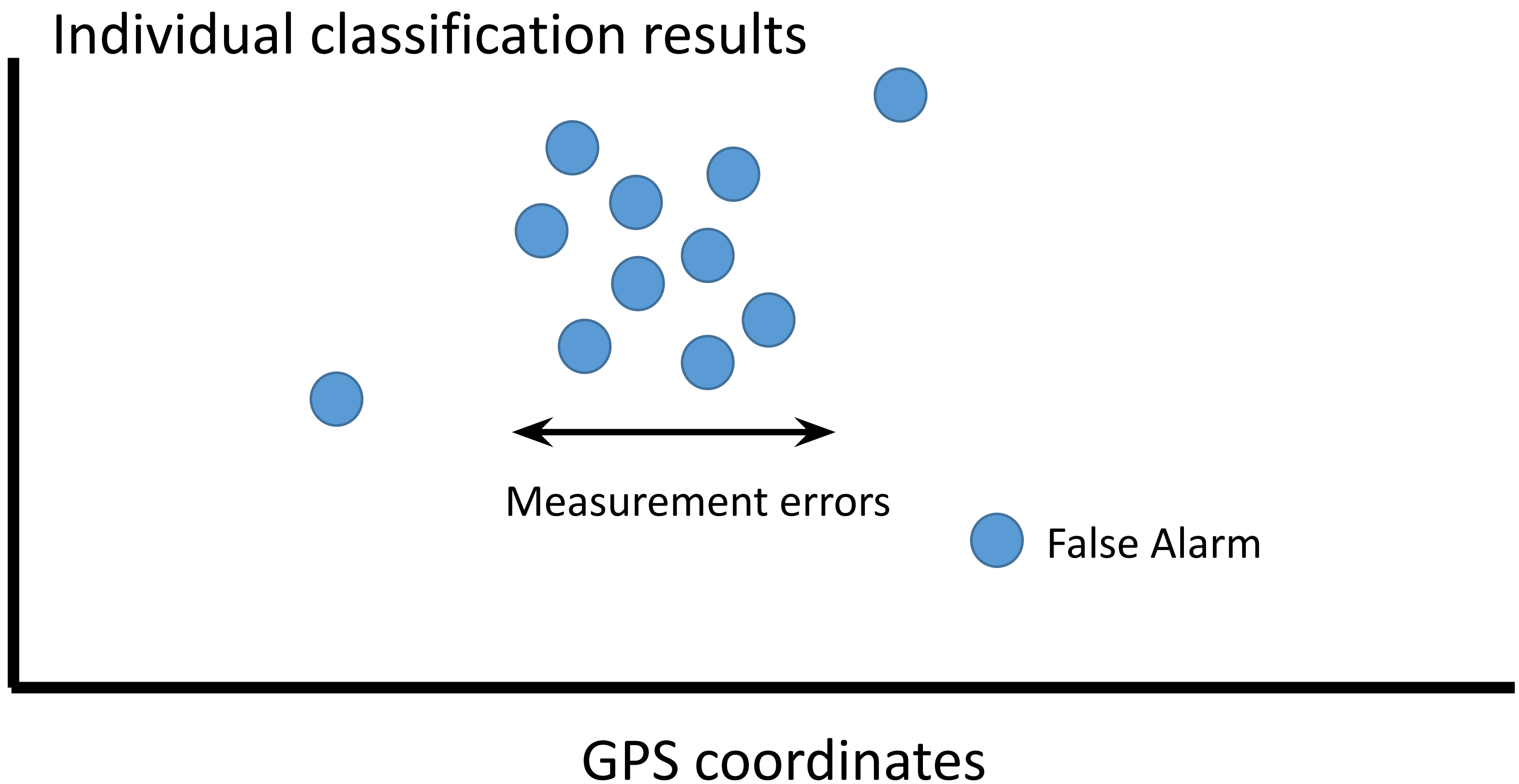

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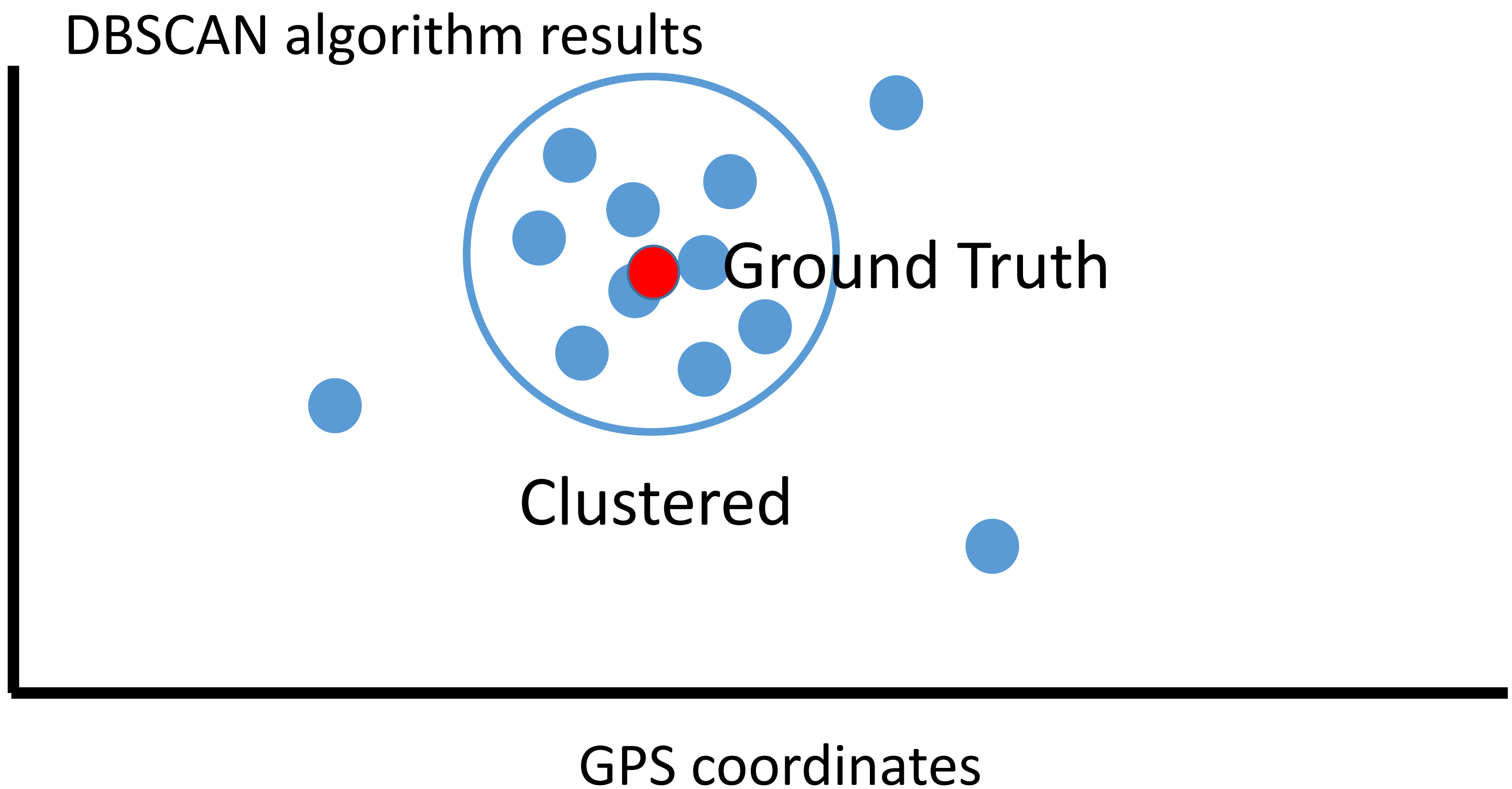


Evaluations

- Evaluation of one-class classification
  - Comparison of one-class classification vs two-class classification
- System performance in different trail data
  - If the system accurately detects risky trails while maintaining generality

Data Collection

Locations

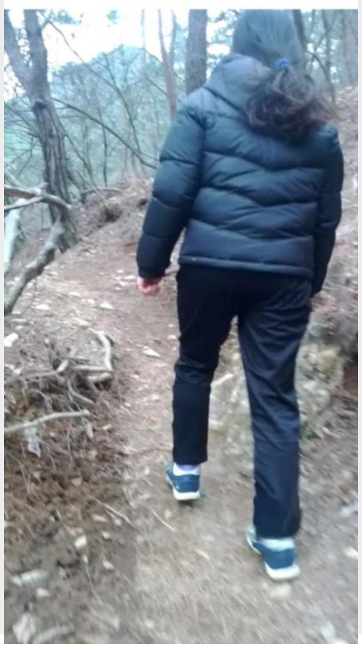
- Gyeryongsan National Prak, Deajeon, South Korea
- Trail A (inter trail experiment) – 5 zones (149m, 109m, 125m, 47m, 27m)
- Trail B and Trail C (intra trail experiment) – 900m, 400m

Participants

- 14 participants (7males and 7 females) whose ages ranged from 22 to 32 years (Mean: 27.4, Std: 2.17)

Devices

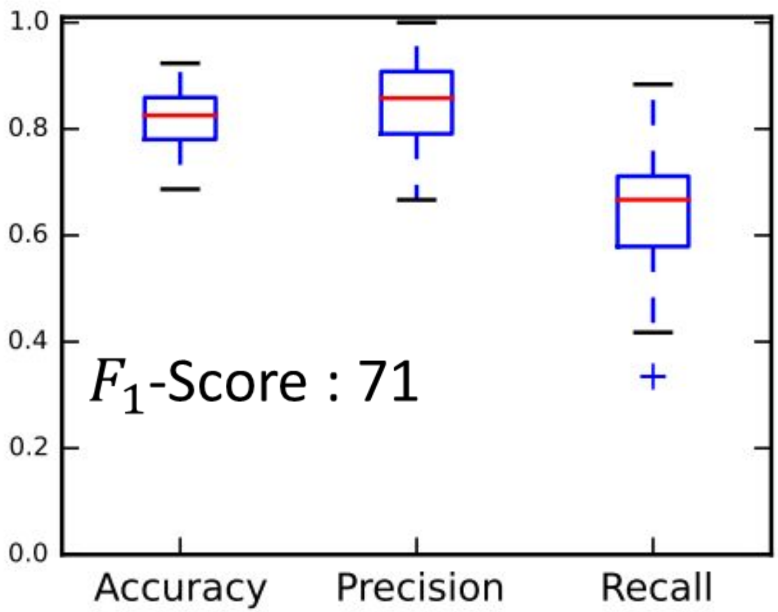
- Smartphones with accelerometer sensor
- Cameras (for ground truth labeling)



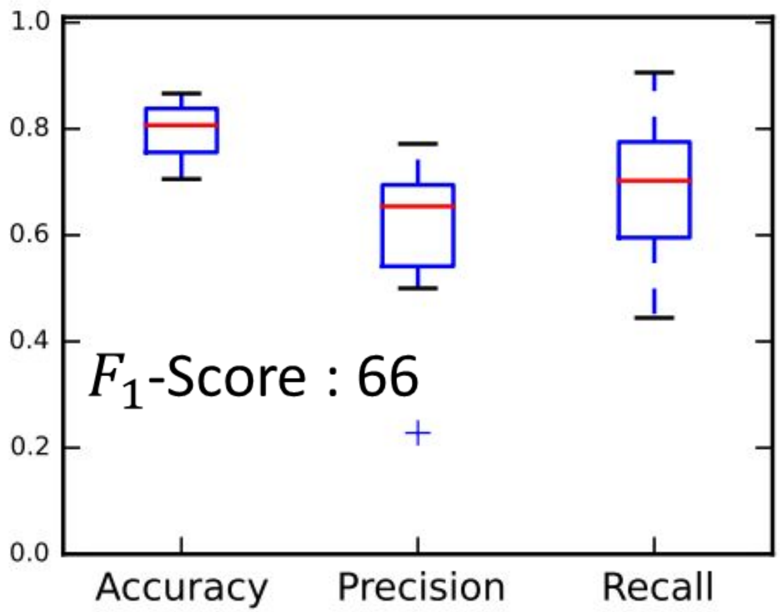
Evaluation Result

Evaluation of one-class classification

One-Class SVM



Two-Class SVM

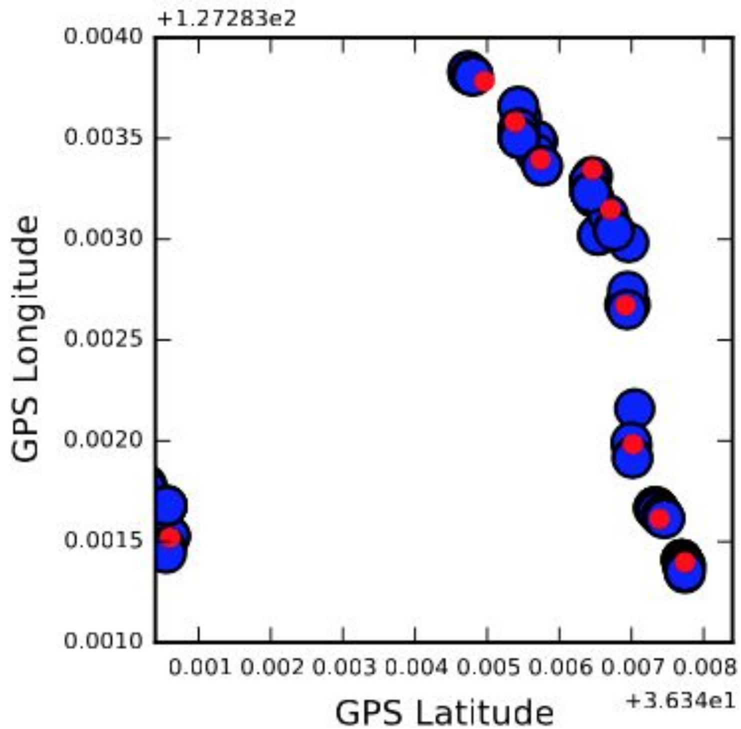


One-Class SVM shows higher test accuracy (F_1-Score)
One-Class SVM achieves higher precision, which is critical for aggregation
Two-Class SVM is less practical (require training data in risky segments)

Evaluation Result

System performance in different trail data

Red : Ground truth Blue – Detected by individual



After data aggregation, our algorithm can detect all 10 risky segments (red-points) with the trained model from the other trail

Summary

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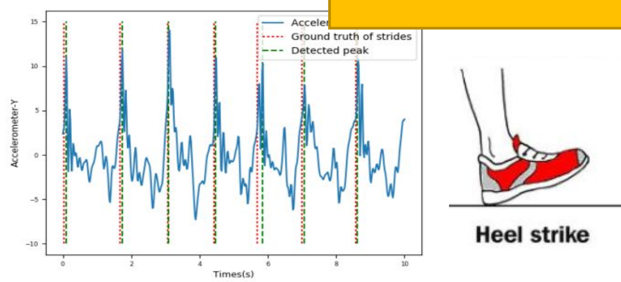
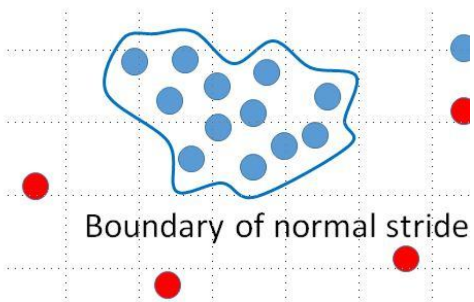
- TrailSense can accurately identify risky trail segments by using crowdsensing

TrailSense

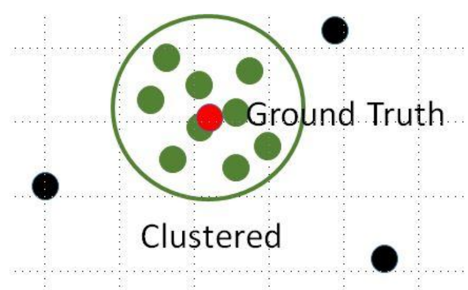
1. Sensor Data Collection



2. Walking Pattern Analysis



3. Stride Classification



4. Crowd Data Aggregation

'Risky Trail'