FALL DETECTION WITH NAÏVE BAYES

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Introduction

- This independent study explores the use of streaming accelerometer data from a commodity based smartwatch device to detect falls.
- The majority of current fall detection applications require specially designed hardware and software, which make them expensive and inaccessible to the general public.
- We collected 270 simulated fall data from 7 different people when they fell on a mattress with different styles.
- We established the baseline accuracy for fall detection that can be achieved by using Naïve Bayes and experimented with different factors that can be used to improve the baseline accuracy.

Methodology

- Collect data with smartphone and smartwatch
 - Android phone and Microsoft Band 2
 - Volunteer fall on a mattress while wearing the watch
- Generate model with collected data
- Classify new data by generated model
- Count consecutive result to decide if there is a fall (heuristic function)
 - A way to predict time series condition while using a point-by-point model

Data Collection

- Implement a mobile app to record data from smartwatch and smartphone
- The mobile app has a button which will mark all incoming data as fall when pressing
 - Less labor intensive
 - The good timing of pressing needs practice to achieve
- 270 falls were collected from 7 different people to increase diversity
- Data frequency is 32ms

Data Processing

- R script to process data.
- Resultant acceleration

 $\sqrt{A_x^2 + A_y^2 + A_z^2}$

- Smin
 - The minimum acceleration in a period of time.
- Smax
 - The maximum acceleration in a period of time.
- Cvfast
 - The resultant difference between SMax and Smin in three directions

Model Generation

- Implement a Java program using Weka's library.
 - Generate the model
- It can also
 - Run simulation
 - Give static result

Work Flow

Raw data

Processed data

(with labeling)

"resultant","cvfast","smax","smin","outcome"

1.07897774215205, 0.644385222430007, 1.07897774215205, 0.94844720398065, "notfall"
0.954836730418577, 0.644385222430007, 1.07897774215205, 0.94844720398065, "notfall"
0.973214327930463, 0.644385222430007, 1.07897774215205, 0.94844720398065, "notfall"
0.978561333521144, 0.644385222430007, 1.07897774215205, 0.94844720398065, "notfall"
1.01840589659131, 0.644385222430007, 1.07897774215205, 0.94844720398065, "notfall"
1.013439072987, 0.182779344275114, 1.02884833417595, 0.94844720398065, "notfall"
1.01354439072987, 0.182779344275114, 1.02884833417595, 0.94844720398065, "notfall"
1.02884833417595, 0.94844720398065, "notfall"
1.02884833417595, 0.94844720398065, "notfall"
1.02884833417595, 0.94844720398065, "notfall"

Work Flow (continued)

- The original data
 - Data is collected, processed and then used to train the model
- The new data
 - Data is collected, processed and then classified by model
 - Count consecutive positive results
 - The thresholds which decide the range of a fall is important and may vary with different version of model

0.629371,6.416013,3.86924,0.402126,' notfall'
0.982495,6.416013,3.86924,0.402126,' notfall'
0.894114,6.416013,3.86924,0.402126,' notfall'
1.029598,6.416013,3.86924,0.402126,' notfall'
1.403548,6.416013,3.86924,0.402126,' notfall'
1.009324,6.188228,3.86924,0.402126,' notfall'
3.86924,6.188228,3.86924,0.402126,' fall'
2.767565,6.188228,3.86924,0.402126,' fall'
3.816125,6.188228,3.86924,0.402126,' fall'
1.996147,6.188228,3.86924,0.402126,' fall'
1.873868,6.188228,3.86924,0.402126,' fall'
1.873868,6.188228,3.86924,0.402126,' fall'
0.56803,6.188228,3.86924,0.402126,' notfall'
1.134361,1.936517,1.701014,0.402126,' notfall'
1.170538,1.936517,1.701014,0.402126,' notfall'
0.402126,1.936517,1.701014,0.402126,' notfall'
1.486898,1.936517,1.701014,0.402126,' notfall'

Heuristic function

```
else if (count is in the range of threshold){
    flagFall = true;
    count = 0;
} else {
    count = 0;
}
```

Experiment

- Run model against test data to get labeled test data, and then count the consecutive positive results to decide if there is a fall.
- Fall and ADL should be tested separately
 - Pure full test
 - Pure ADL test
- 2/3 of collected fall data was used as train data for Naïve Bayes model.
- 1/3 of collected fall data was used as test data for pure full

Experiment (continued)

- 1. Baseline version
 - The first version of model only trained with fall data
- 2. Improved version by adding ADL data into training data
 - Relate with future plan which automatically collects false positive data from the users and re-trains the model
- 3. Improved version by using heuristic function on top of whole system to check phone acceleration
 - If the user falls and the phone is in the user's pocket, there should be acceleration happening

Experiment – baseline

- Train data
 - 2/3 of fall data used as train data for Naïve Bayes model.
- Test data (pure fall)
 - 1/3 of fall data used as test data for pure full
- Test data (ADL)
 - Quick sitting
 - Waving
 - Throwing
 - Jogging

Result (Experiment – baseline)

Pure fall

Threshold	Detected fall	Accuracy
6~50	75/90	83.33%
5~50	77/90	85.56%
4~50	82/90	91.11%
3~50	85/90	94.44%

Result (Experiment – baseline)

Pure ADL

Threshold	False positive	Accuracy
6~50	1/90 (Ow 1j)	98.89%
5~50	4/90 (Ow 4j)	95.56%
4~50	14/90 (2w 12j)	84.44%
3~50	23/90 (7w 16j)	74.44%

Result (Experiment – baseline)

Overall

Threshold	Overall Accuracy
6~50	91.11%
5~50	90.56%
4~50	87.78%
3~50	84.44%

Train data

- 2/3 of fall data
- Additional ADL data
- Test data (pure fall)
 - 1/3 of fall data used as test data for pure full
- Test data (ADL)
 - Quick sitting
 - Waving
 - Throwing
 - Jogging

Pure fall

Threshold	Detected fall	Accuracy
6~50	74/90	82.22% ▼
5~50	76/90	84.44% ▼
4~50	80/90	88.89% ▼
3~50	84/90	93.33% ▼

Pure ADL

Threshold	False positive	Accuracy
6~50	1/90 (Ow 1j)	98.89%
5~50	3/90 (0w 3j)	96.69% ▲
4~50	9/90 (Ow 9j)	90.00% 🔺
3~50	18/90 (2w 16j)	80.00% 🔺

Overall

Threshold	Overall Accuracy
6~50	90.56% 🔺
5~50	90.56%
4~50	89.44% ▲
3~50	86.67% ▲

- Same train data and test data as ADL improved experiment.
- Add a heuristic function on top of the whole system to double check if a predicted fall is a real fall.
 - Check resultant acceleration from phone
 - Set (resultant acceleration > 5.0) as the condition

Pure fall

Threshold	Detected fall	Accuracy
6~50	74/90	82.22%
5~50	76/90	84.44%
4~50	80/90	88.89%
3~50	84/90	93.33%

Pure ADL

Threshold	False positive	Accuracy
6~50	1/90 (Ow 1j)	98.89%
5~50	2/90 (0w 2j)	97.78% 🔺
4~50	8/90 (0w 8j)	91.11% 🔺
3~50	14/90 (Ow 14j)	84.44% ▲

Overall

Threshold	Overall Accuracy
6~50	90.56%
5~50	91.11% 🔺
4~50	90.00% 🔺
3~50	88.89% 🔺

Best combination

Improved version with phone acceleration

Threshold	Overall Accuracy	Fall Accuracy
4~50	90.00%	88.89%
3~50	88.89%	93.33%

Conclusion

- Adding more ADL data does improve the performance of predicting ADL, but it's a tradeoff which may weaken the ability of predicting fall.
- Considering phone acceleration on top of the prediction can filter out more ADLs, which reduces false positive rate. Waving can be filtered out well.
 - Allowing us to set threshold [3, 50] while still maintaining decent overall accuracy
- The jogging ADL is hard to perfectly handled. If the user can avoid jogging, the app will have a very good accuracy.