Activity Recognition using Cell Phone Accelerometers

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Introduction

- Today's mobile devices are filled with a number of sensors
  - i.e. GPS, audio sensors, light sensors, accelerometers
- These sensors open up new opportunities
  - Especially in data mining research and applications

Accelerometers

- All modern smartphones contain accelerometers
  - Specifically tri-axial accelerometers (x,y,z)
- Accelerometers are capable of detecting device orientation
- Accelerometers included in devices initially to support:
  - Advanced game play
  - Automatic screen rotation
- But there are a number of other applications for this sensor

Goal

- Create a system which uses this data to perform activity recognition
  - Using the commercially available accelerometer in smartphones

Related Work

- Accelerometer-based activity recognition is not new
- Earliest works (i.e. Bao & Intille) use multiple accelerometers
  - Used 5 bi-axial accelerometers worn by each user
  - Found that sensor on thigh was the most powerful
- Another work (Krishna et. al.) claim that multiple accelerometers necessary for activity recognition

Related Work

- Combination of accelerometers and other sensors
  - Use heart monitor data (Tapia et. al.)
  - Parkka et. al. created system using 20 different sensors
  - Combination of accelerometer, angular velocity sensor, and digital compass (Lee and Mase)
  - “eWatch” devices
- These systems are not very practical

Related Work

- Focus of this work is on using a single accelerometer
  - Some work has been done on that
- Work has been done to use the smartphones
  - Some work just used the phone as a data collector from external sensors (i.e. “MotionBands”)
  - Others have used multiple phone sensors
    - Various degrees of accuracy
    - Model is trained for a specific user, not universal

Methodology (Data Collection)

- Data collected from 29 subjects
- Phone was carried in the front pant leg pocket
  - For all activities
- Accelerometer data collected every 50ms
  - 20 samples/second

Methodology

- Raw time-series data cannot be used with classification algorithms
- Data divided into 10-second segments
  - Chose duration because it captured repetitions of motion
- Generated features based on the 200 readings in each segment

Methodology (Feature Generation)

- Average[3]: Average acceleration (for each axis)
- Standard Deviation[3]: Standard deviation (for each axis)
- Average Absolute Difference[3]: Average absolute difference between the value of each of the 200 readings within the ED and the mean value over those 200 values (for each axis)
- Average Resultant Acceleration[1]: Average of the square roots of the sum of the values of each axis squared $\sqrt{(x_i^2 + y_i^2 + z_i^2)}$ over the ED
- Time Between Peaks[3]: Time in milliseconds between peaks in the sinusoidal waves associated with most activities (for each axis)
- Binned Distribution[30]: We determine the range of values for each axis (maximum – minimum), divide this range into 10 equal sized bins, and then record what fraction of the 200 values fell within each of the bins.

Methodology (Activities)

- Six activities considered
  - Walking, jogging, ascending stairs, descending stairs, sitting, and standing
- Repetitive motions should make activities easier to identify

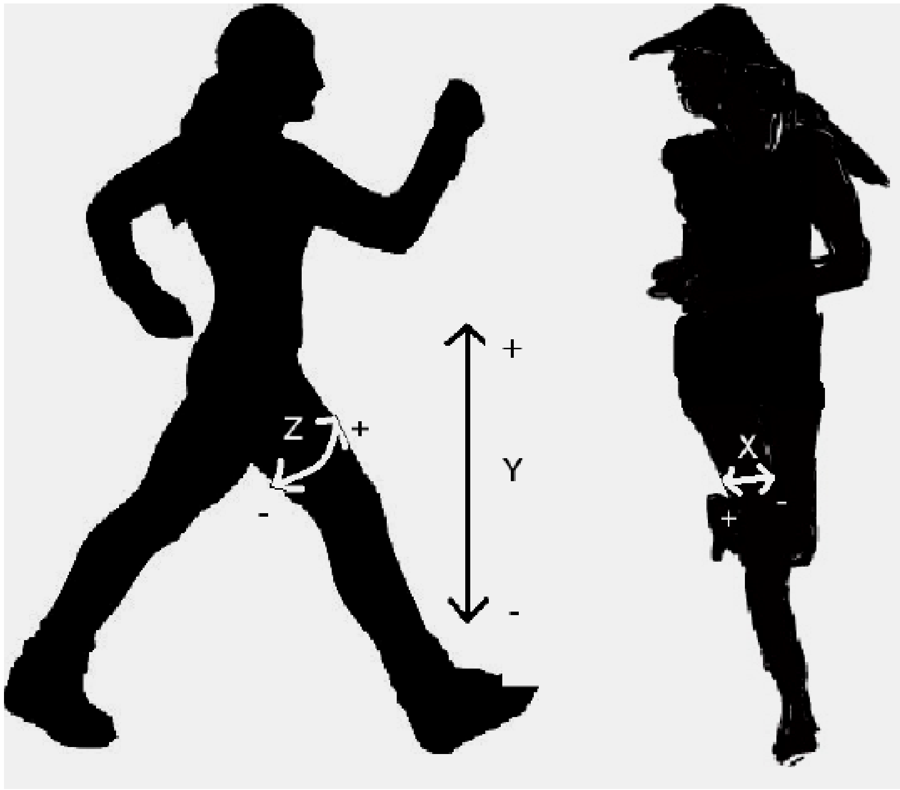
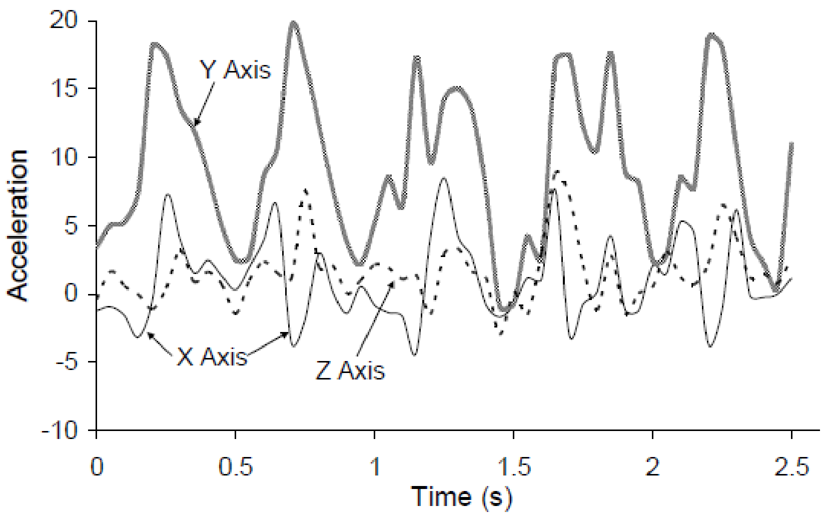
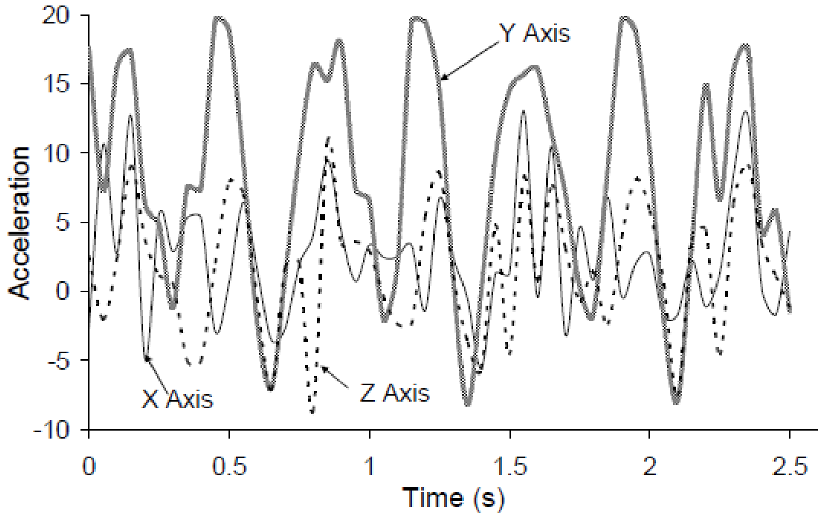


Figure 1: Axes of Motion Relative to User

Methodology (Activities)

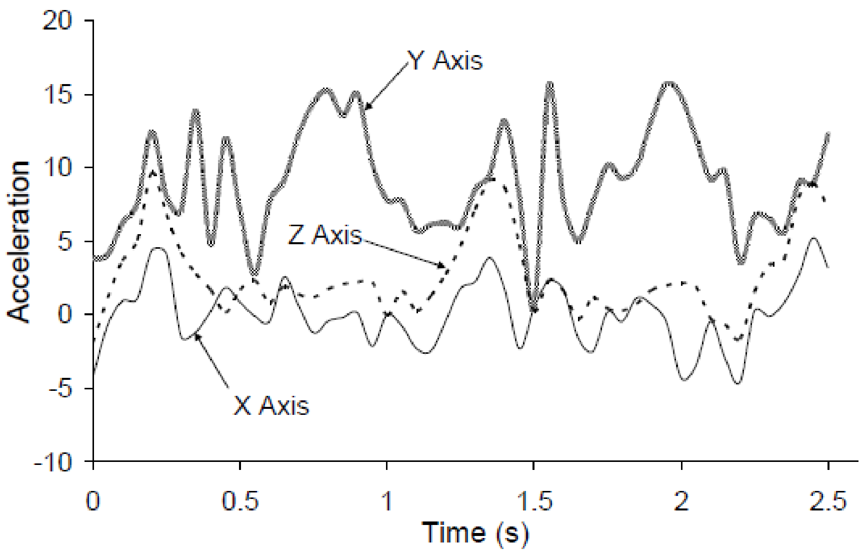


(a) Walking

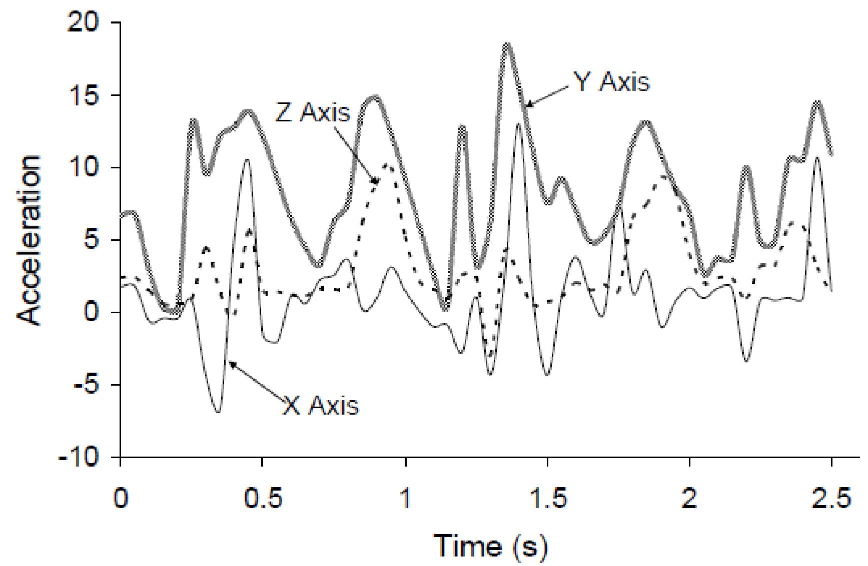


(b) Jogging

Methodology (Activities)

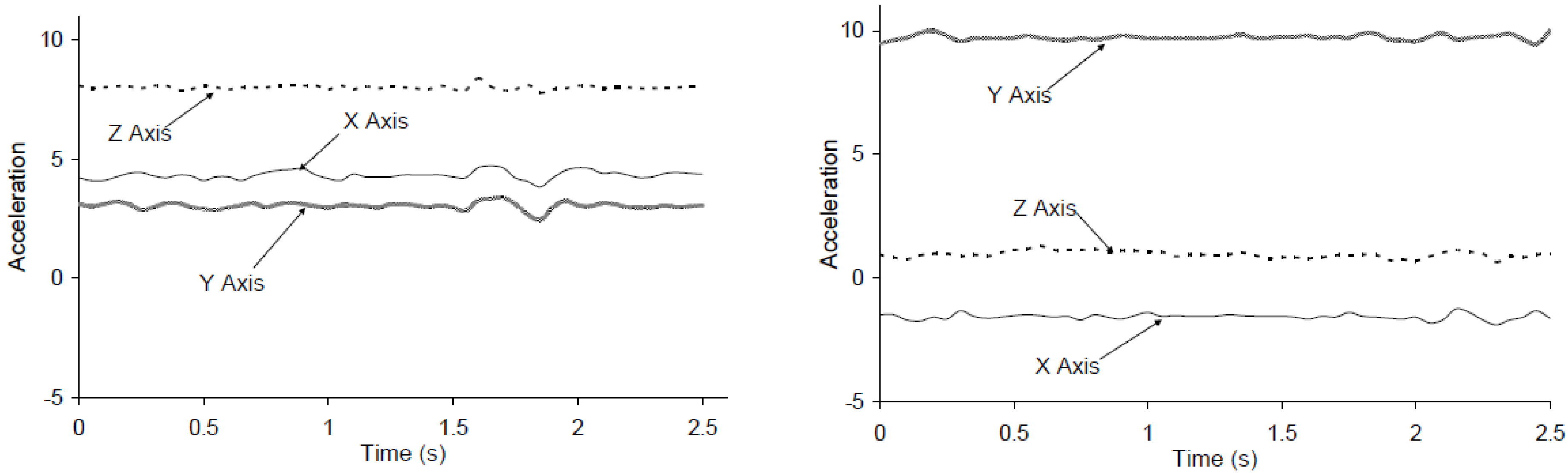


(c) Ascending Stairs



(d) Descending Stairs

Methodology (Activities)



(e) Sitting **(f) Standing**

Results

- 3 classification techniques using WEKA
- Able to achieve high accuracies (>90%) for most activities
- Stair climbing activity difficult to identify

Table 2: Accuracies of Activity Recognition

	% of Records Correctly Predicted			
	J48	**Logistic Regression**	**Multilayer Perceptron**	**Straw Man**
Walking	89.9	**93.6**	91.7	37.2
Jogging	96.5	98.0	**98.3**	29.2
Upstairs	59.3	27.5	**61.5**	12.2
Downstairs	**55.5**	12.3	44.3	10.0
Sitting	**95.7**	92.2	95.0	6.4
Standing	**93.3**	87.0	91.9	5.0
Overall	85.1	78.1	**91.7**	37.2

Closer Look at Results

Table 3: Confusion Matrix for J48

		Predicted Class					
		Walk	Jog	Up	Down	Sit	Stand
Actual Class	Walk	**1513**	14	72	82	2	0
	Jog	16	**1275**	16	12	1	1
	Up	88	23	**323**	107	2	2
	Down	99	13	92	**258**	1	2
	Sit	4	0	2	3	**270**	3
	Stand	4	1	2	7	1	**208**

Table 4: Confusion Matrix for Logistic Regression

		Predicted Class					
		Walk	Jog	Up	Down	Sit	Stand
Actual Class	Walk	**1575**	14	53	36	2	3
	Jog	15	**1294**	6	6	0	0
	Up	277	36	**150**	77	1	4
	Down	259	6	136	**57**	3	4
	Sit	1	0	4	11	**260**	6
	Stand	3	1	7	3	15	**194**

Table 5: Confusion Matrix for Multilayer Perceptron

		Predicted Class					
		Walk	Jog	Up	Down	Sit	Stand
Actual Class	Walk	**1543**	5	73	60	1	1
	Jog	3	**1299**	16	3	0	0
	Up	84	24	**335**	98	2	2
	Down	108	10	136	**206**	2	3
	Sit	0	2	4	1	**268**	7
	Stand	1	0	5	4	8	**205**

Results

- To limit confusion between ascending and descending
  - Combine both activities together
- Results are much better
  - But stair climbing is still difficult to identify

Table 6: Confusion Matrix for J48 Model (Stairs Combined)

		Predicted Class					Accur. (%)
		Walk	Jog	Stairs	Sit	Stand	
Actual Class	Walk	**1524**	7	148	2	2	90.6
	Jog	10	**1280**	31	0	0	96.9
	Stairs	185	33	**784**	4	4	77.6
	Sit	4	0	2	**272**	4	96.5
	Stand	3	1	10	0	**209**	93.7

Conclusion

- Demonstrated that activity detection can be highly accurate using smart phone accelerometers
  - Most activities recognized over 90% of the time

Future Work

- Platform and data to be available to public
- Activity recognition improvements
  - Recognize bicycling and car-riding
  - Obtain more training data
  - Additional and more sophisticated features
  - Look at impact of carrying phone not in pant pocket
- Look at possibility of displaying results in real-time

References

- Bao, L. and Intille, S. 2004. Activity Recognition from User-Annotated Acceleration Data. *Lecture Notes Computer Science 3001*, 1-17.
- **J48 Classification** *http://monkpublic.library.illinois.edu/monkmiddleware/public/analytics/decisiontree.html*
- **Logistic Regression, Wikipedia,** http://en.wikipedia.org/wiki/Logistic_regression
- **Multilayer Perceptron, Wikipedia,** http://en.wikipedia.org/wiki/Multilayer_perceptron

QUESTIONS?