34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

Activity Recognition in Planetary Navigation Field Tests Using Classification Algorithms Applied to Accelerometer Data

Wen Song[1], Carl Ade[2], Ryan Broxterman[2], Thomas Barstow[2], Thomas Nelson[1], and Steve Warren[1]
[1]Department of Electrical & Computer Engineering, Kansas State University, Manhattan, KS, USA
[2]Department of Kinesiology, Kansas State University, Manhattan, KS, USA

Abstract—**Accelerometer data provide useful information about subject activity in many different application scenarios. For this study, single-accelerometer data were acquired from subjects participating in field tests that mimic tasks that astronauts might encounter in reduced gravity environments. The primary goal of this effort was to apply classification algorithms that could identify these tasks based on features present in their corresponding accelerometer data, where the end goal is to establish methods to unobtrusively gauge subject well-being based on sensors that reside in their local environment. In this initial analysis, six different activities that involve leg movement are classified. The k-Nearest Neighbors (kNN) algorithm was found to be the most effective, with an overall classification success rate of 90.8%.**

Keywords—**accelerometer, activity recognition, feature detection, performance classification**

I. Introduction

Many types of small sensors have emerged rapidly in recent years given improvements in MEMS technology. Among them, accelerometers have drawn much attention due to increases in their accuracy and availability. In many products, accelerometers are bundled with wireless transmission features in order to increase their usefulness when mounted, e.g., on a person's body. Previously, accelerometer-based analyses have been applied to step length estimation [1], gait analysis and fatigue determination [2,3], personal dead reckoning navigation systems [4] in place of GPS- or compass-based navigation when satellite signals are unavailable, such as for a first responder in a building [5] or within the context of dangerous missions such as military engagements.

Wireless accelerometers have also been applied for user activity determination. Various studies have been conducted with different setups, where one or more accelerometers have been placed on different parts of body to record acceleration, and then these recorded data are processed to extract useful information regarding these activities and their identification. Such activities range from single part movement, such as Kung Fu gestures in the arm [6], to whole body movements such as walking, running, and cycling [7-9]. In order to relieve the user from the trouble of wearing such sensors towards a goal of estimating their daily activities, S. Wang and N. Chen [10] proposed to place these sensors on the objects associated with each activity (e.g., a telephone, water glass, and pen for identifying the processes of making a phone call, drinking, and writing, respectively). However, this methodology is still novel and heavily relies on an omnipresent sensor network as well as data procession center to supply the system.

While detecting these activities, research groups often incorporate multiple accelerometers on major body parts or joints. Popular locations include the thigh, arm, hip, and waist, since they represent action in the critical parts of the body. However, in certain situations, these locations are inaccessible or may be compromised. The goal is to minimize the accelerometer quantity while achieving good results.

This paper presents an initial study to classify types of field-test activities using single-accelerometer data. Information regarding these activities is presented in Section II. Data acquisition and feature extraction methods are introduced in Section III, along with the algorithms used to train the data. Section IV presents the classification results and some discussion points. Finally, Section V notes the limitations of this approach and presents future work.

II. Background

Planetary Navigation Field Tests (PNFTs) have been designed for an ongoing NASA project to assess subject fatigue when performing physical tasks [11,12]. Various physiologic sensors are worn by each subject during these timed tests, including a heart rate monitor, accelerometer, and portable gas exchange system. These data are then studied with a goal of correlating task failure with physiologic condition. The overall goal is to use these statistical results to predict an astronaut's ability to successfully accomplish such tasks, eventually in a reduced gravity environment.

PNFT activities are designed to emulate potential tasks an astronaut might encounter in space or on another planet. The six tasks addressed here form a continuous circuit that is run repeatedly by a subject until the end of the test. The definition of each task follows:

1. **Ladder Climb.** Subjects ascend/descend scaffolding.
2. **Agility Cones.** Subjects move forward and backward through six cones.
3. **Stair Climb.** Subjects climb a set of stairs and then descend them backwards.

Manuscript received March 15, 2012. This work was supported by the NASA Human Research Program, Johnson Space Center, Exploration Systems Mission Directorate, Houston, TX. Any opinions, findings and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of NASA.

4. **Horizontal Climb.** Subjects climb horizontally along a wall using hand and foot grips.

5. **Equipment Lift.** Subjects lift two 10 lb and two 20 lb equipment boxes from waist- to eye-level and from ground- to waist-level, respectively, then lower them in reverse order to the starting position.

6. **Step-Entry Maneuver.** Subjects move laterally and periodically step over ropes and duck under poles to simulate stepping over and under a hatch entry.

The task order and physical layout are illustrated in Fig. 1. Each test cycle starts at the ladder climb and continues counter-clockwise through all of the other tasks. Each subject is required to accomplish all 6 tasks sequentially through the cycle, and each experiment contains 20 repeated cycles. Critical information such as time duration for each task, heart rate, O_2 and CO_2 concentrations (for metabolic rate extraction), and 3-axis acceleration are recorded during each experiment.

In this scenario, acceleration quantitatively mirrors the intensity of an activity, so the original goal was to employ accelerometers to record body movement for a known activity, since these data might at some point indicate fatigue and potential failure. The secondary goal is to then see if acceleration data can be used to identify the tasks that these subjects accomplish, as this provides a means to automate the process of tracking both subject well-being and context.

Difficulties inherent in recognizing such tasks from one another include the fact that all six of these activities share similarities in terms of movement patterns. The step-entry maneuver, ladder climb, agility cones, and stair climb all involve an element of running or lower body movement. All activities except for the agility cones involve arm movement. Finally, all of these activities are high intensity. Such analogies among the activities can pose challenges for the classification algorithms.

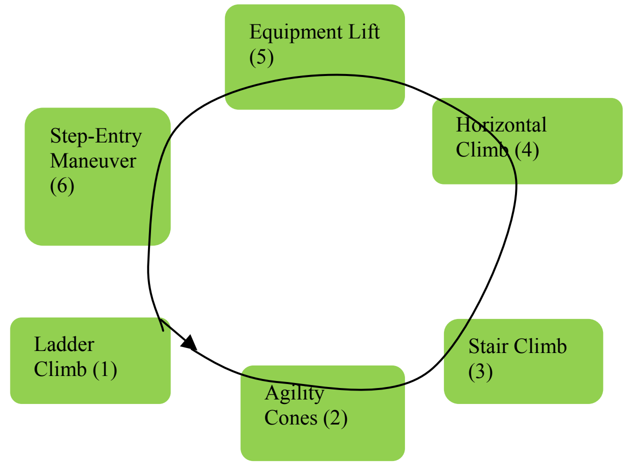

Fig. 1. Planetary navigation field test task cycle.

III. Methods

A. Zephyr Health Monitoring System

A Zephyr BioHarness, a commercial health monitoring device [13], was used to record physiologic data for these assessments, which involve two test subjects. These data

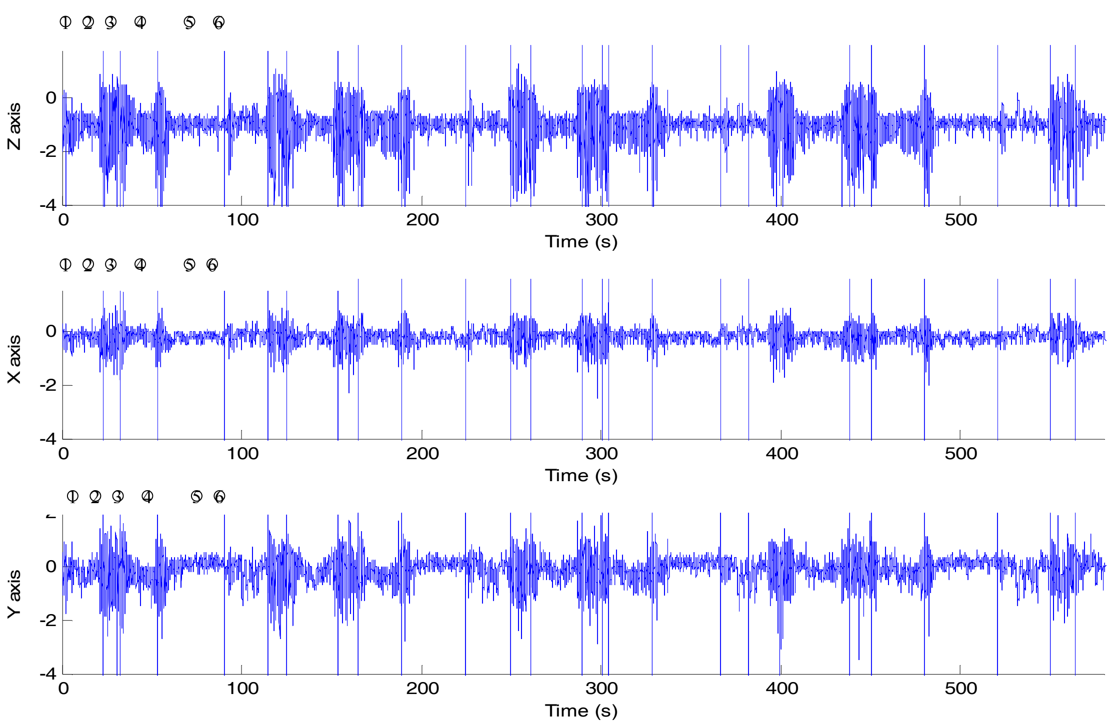

Fig. 2. Sample 3- axis acceleration data from 4 cycles of movement.

include heart rate (via an electrocardiogram (ECG)) and skin surface temperature. Additionally, a tri-axial accelerometer is embedded inside the device and sends acceleration data at a sampling rate of 50 Hz. To achieve optimal heart rate data, the BioHarness is worn around the subject's chest. Accelerometer placement on the chest differs from previous work, where such a sensor might be mounted, e.g., on a limb to reflect precise movement for that part of the body. The chest-worn accelerometer is oriented such that the z-axis points upward, the x-axis points forward, and the y-axis points to the subject's left. A sample data set that includes 4 rounds of activity, with six tasks per round, is depicted in Fig. 2, where the first grouping of tasks (① through ⑥) is labeled in the upper left portion of each axis.

B. Single Activity Data Acquisition

During a normal field test, each task is performed once per cycle, and the duration of that task is short – often a couple of seconds. In addition, after finishing an activity, the subject is required to run for a short distance to the next task station; this ambiguous task separation adds an additional burden to the classification process. Therefore, new training sets of data for each activity were acquired separately, with one person performing each task repeatedly for about 1 minute. Each piece of the data is clearly labeled by activity and used for classification and identification.

C. Feature Extraction

Raw training data are pre-processed by extracting several features based on a window size of 2 seconds with an overlap of 1 second, i.e., 100 samples with an overlap of 50 samples. A window size selected to cover the periodicity of an activity plus an overlap of 50% between consecutive windows has been demonstrated to yield optimal results in previous work [14]. Four basic features (mean value, variance, energy, and entropy) are extracted for each axis, yielding a total of 12 features for the 3 accelerometer axes.

Since all activities involve periodicity, an energy calculation is applied to characterize the frequency components of each activity. This quantity is represented by the normalized sum of frequency components over a window, where the frequency components, x_i, are the complex coefficients obtained by calculating the Fast Fourier Transform (FFT) of the time domain data:

$$Energy = \frac{\sum |x_i|^2}{window\ width} \quad (1)$$

Entropy characterizes the consistency in an activity. An activity with a high repeated frequency, e.g., the agility cones, ends up with low entropy, whereas a task with irregular motion and randomness is prone to have higher entropy. Entropy helps to differentiate activities with similar energy consumption.

$$Entropy = \frac{\sum -|x_i| \ln(|x_i|)}{window\ width} \quad (2)$$

D. Classification Algorithms

Three major classification algorithms were used to classify these activities:

- C4.5 Decision Tree
- k-Nearest Neighbors
- Support Vector Machine

These classifications were realized using the WEKA toolkit [15]. A 10-fold cross-validation test method was adopted when training and validating the classification for each algorithm. Specifically, each data set was divided into 10 parts, where 9 of them were used to train the classifier and the remaining unused part was applied to assess the effectiveness of the classifier.

IV. Results and Discussion

The accuracy for each classification method is listed in Table I. All three algorithms exhibit high accuracy, while the k-Nearest Neighbors algorithm demonstrates the highest recognition rate.

TABLE I
ACCURACY OF EACH CLASSIFIER

C4.5 Decision Tree	89.94%
k-Nearest Neighbors	90.77%
Support Vector Machines	86.40%

Even though all activities share similar patterns, they are fairly well identified with a single tri-axial accelerometer. Table II provides the percentage of correct assessments for each activity. Activities with more regular patterns, stable periodicity, and no interference between the upper and lower body, as the result suggests (such as agility cones, which is similar to normal running, and the step–entry maneuver, whose major motion is regular jumping), are prone to be identified with low ambiguity. Otherwise, those with high interplay between arms and legs reveal more irregularity and are less likely to be well-classified, such as ladder climbing and horizontal climbing. Aside from the fact that it is the one task that is different in nature from the other activities (since there is no lower body movement at all), the equipment lift is the activity identified with the least overall accuracy. Sensor placement is arguably the main reason for misjudging this activity. The bending down and raising up movement is mistaken to be leg movement that is similar to other activities.

TABLE II
CORRECTNESS OF IDENTIFICATION OF EACH ACTIVITY

	C4.5	kNN	SVM	Overall
Cones	96.30%	98.15%	98.15%	97.53%
Ladder	78.85%	78.85%	94.23%	83.97%
Lift	82.14%	80.95%	72.02%	78.37%
Step	98.61%	98.61%	96.53%	97.92%
Stair	93.96%	94.51%	96.70%	95.05%
Wall	81.11%	80.00%	32.22%	64.44%

Tables III to V display the confusion matrices for the different tasks as a function of classification algorithm. From these tables, it can be noted that ladder climbing and stair climbing both involve a stepping action and that they are confused with each other but not with the other tasks. Most of the false classifications for equipment lifting fall into the category of ladder climbing, since both activities have no forward/backward (x-axis) movement. The same situation applies to the horizontal climb. It is largely mis-tagged as ladder climbing, since both activities involve no major y-axis component, and the x-axis movement in horizontal climbing is similar to upper body tilting when the gravitational point shifts between the left side and the right side of the body during ladder climbing.

TABLE III
CONFUSION MATRIX FROM C4.5 DECISION TREE

	Classified As					
Activity	Cones	Ladder	Lift	Step	Stair	Wall
Cones	52	2	0	0	0	0
Ladder	0	82	10	1	3	8
Lift	0	9	138	2	11	8
Step	1	0	0	142	0	1
Stair	0	7	4	0	171	0
Wall	0	11	6	0	0	73

TABLE IV
CONFUSION MATRIX FROM KNN

	Classified As					
Activity	Cones	Ladder	Lift	Step	Stair	Wall
Cones	53	1	0	0	0	0
Ladder	0	82	7	2	0	13
Lift	0	12	136	4	9	7
Step	0	0	2	142	0	0
Stair	0	2	3	5	172	0
Wall	0	8	7	1	2	72

TABLE V
CONFUSION MATRIX FROM SVM

	Classified As					
Activity	Cones	Ladder	Lift	Step	Stair	Wall
Cones	53	1	0	0	0	0
Ladder	0	98	4	0	2	0
Lift	0	43	121	0	4	0
Step	0	1	4	139	0	0
Stair	0	4	2	0	176	0
Wall	0	60	0	0	1	29

V. CONCLUSION

In this effort, the investigators applied classification algorithms to accelerometer data acquired from a set of six field tests to see if the features extracted from these data sets were sufficient to allow the activities to be distinguished from one another. Each of the three classification approaches demonstrated acceptable overall accuracy, even though physical elements of the field tests were quite similar in nature (e.g., periodic stepping movements). These results are encouraging, as they imply that accelerometer data may be useful to identify individual activities (at least from a pool of known possible activities) without requiring additional action from the user. In the planetary scenario that drove the choice of tasks for this investigation, the use of accelerometer data to identify both the type of task as well as the level of fatigue experienced by the subject is a promising step forward toward the automated assessment of astronaut health.

REFERENCES

[1] S. Y. Cho, K.W. Lee, C.G. Park and J.G.Lee, "A Personal Navigation System Using Low-Cost MEMS/GPS/Fluxgate," *59th Annual Meeting - CIGTF, 22nd Guidance Test Symposium*, June 23-25, 2003.
[2] S. Meardon, J. Hamill and T. Derrick, "Running Injury and Stride Time Variability Over a Prolonged Run", *Gain & Posture*, vol. 33, pp. 36-40, 2011.
[3] R. Bris, V. Billat, B. Auvinet, D. Chaleil, L. Hamard and E. Barrey, "Effect of Fatigue on Stride Pattern Continuously measured by an Accelerometric Gait Recorder in Middle Distance Runners" *The Journal of Sports Medicine and Physical Fitness*, vol. 46, no. 2, p. 227, June 2006.
[4] L. Ojeda, J. Borenstein, "Non-GPS Navigation for Security Personnel and First Responders" *Journal of Navigation*, vol. 60, no. 3, pp. 391-407, Sept. 2007.
[5] V. Renaudin, O. Yalak, P. Tome and B. Merminod, "Indoor Navigation of Emergency Agents" *European Journal of Navigation*, vol. 5, no. 3, July 2007.
[6] G.S. Chambers, S. Venkatesh, G.A.W. West, and H.H. Bui. "Hierarchical recognition of intentional human gestures for sports video annotation" *Proceedings of the 16th International Conference on Pattern Recognition*, vol. 2, pp. 1082-1085, IEEE Press, 2002.
[7] N. Ravi, N. Dandekar, P. Mysore and M. Littman, "Activity Recognition from Accelerometer Data" *American Association for Artificial Intelligence*, 2005.
[8] A. Khan, Y. K. Lee, S. Y. Lee and T.S. Kim, "A Triaxial Accelerometer-Based Physical-Activity Recognition via Augmented-Signal Features and a Hierarchical Recognizer" *IEEE Transactions on Information Technology in Biomedicine*, vol. 14, no. 5, Sept. 2010.
[9] L. Bao, S. Intille "Activity recognition from User- Annotated Acceleration Data" *Pervasive Computing*, LNCS 3001, pp 1-17, 2004..
[10] S. Wang, J. Yang, N. Chen, X. Chen, Q. Zhang, "Human Activity Recognition with User- Free Accelerometers in the Sensor Networks" *Neural Networks and Brain*, 2005, ICNN&B '05.
[11] Ade, Carl J., Ryan M. Broxterman, Gary L Gadbury, Dale Schinstock, Steve Warren, and Thomas J. Barstow. "Standardized Exercise Test to Evaluate Planetary Mission Readiness," HRP 2012, *NASA Human Research Program Investigators' Workshop*, February 14–16, 2012,
[12] Broxterman, Ryan M., Carl J. Ade, Gary L Gadbury, Dale Schinstock, Steve Warren, and Thomas J. Barstow. "10-km Walkback Performance Predicted fom Standardized Exercise Tests," HRP 2012, *NASA Human Research Program Investigators' Workshop*, February 14–16, 2012,
[13] Zephyr Technology, http://www.zephyr-technology.com/.
[14] R.W. DeVaul and S. Dunn. "Real-Time Motion Classification for Wearable Computing Applications" *Technical Report*, MIT Media Laboratory, 2001.
[15] R. Bouckaert, E. Frank, M. Hall, et al. WEKA Manual for Version 3-6-0.