Characterization of Wheelchair Maneuvers based on Noisy Inertial Sensor Data: A Preliminary Study

Jicheng Fu, Tao Liu, Maria Jones, Gang Qian, Yih-Kuen Jan

Abstract— **A wheelchair user's activity and mobility level is an important indicator of his/her quality of life and health status. To assess the activity and mobility level, wheelchair maneuvering data must be captured and analyzed. Recently, the inertial sensors, such as accelerometers, have been used to collect wheelchair maneuvering data. However, these sensors are sensitive to noises, which can lead to inaccurate analysis results. In this study, we analyzed the characteristics of wheelchair maneuvering data and developed a novel machine-learning algorithm, which could classify wheelchair maneuvering data into a series of wheelchair maneuvers. The use of machine-learning techniques empowers our approach to tolerate noises by capturing the patterns of wheelchair maneuvers. Experimental results showed that the proposed algorithm could accurately classify wheelchair maneuvers into eight classes, i.e., stationary, linear acceleration/deceleration, linear constant speed, left/right turns, and left/right spot turns. The fine-grained analysis on wheelchair maneuvering data can depict a more comprehensive picture of wheelchair users' activity and mobility levels, and enable the quantitative analysis of their quality of life and health status.**

I. INTRODUCTION

Information regarding wheelchair maneuvering characteristics is essential for revealing wheelchair users' activity and mobility level [1], which is an important indicator of their quality of life and health status [2, 3]. In addition, wheelchair maneuvering characteristics are critical for studying safety issues as wheelchair-related accidents frequently occur, and some may lead to serious injuries [4]. Despite its importance, research on capturing and analyzing wheelchair maneuvering characteristics is still a relatively under-investigated area as there is only limited information on this topic [1, 5, 6].

Recently, the inertial sensors, such as accelerometers, have been used to collect wheelchair maneuvering data [7, 8]. The use of accelerometers is convenient due to the availability of commercial products, and also simplifies the experimental setup [7]. However, a big challenge associated with the use of accelerometers is that they are sensitive to noises. Even when an accelerometer is stationary, it still generates sensor readings due to the rotation of the earth, gravity, and/or other environmental noises. The current research uses low-pass filters to remove noises that have a frequency higher than a predefined cut-off threshold [7]. However, noises with a frequency lower than the cut-off threshold may still exist. As a result, the noises will make it difficult to even determine whether the wheelchair is stationary or moving [7].

In this study, we aim to address this challenge by developing a machine-learning algorithm, which can accurately classify wheelchair maneuvers, such as the idle state (i.e., stationary), accelerations/decelerations, left/right turns, etc. The use of machine learning techniques can counteract noises by capturing the patterns of wheelchair maneuvers. By distinguishing the maneuver of idle state from other non-idle maneuvers, we can measure a wheelchair user's activity (e.g., maximum continuous maneuvering time, number of starts/stops, etc.) and mobility (e.g., active hours), which are the desired information studied in the current research [1-3, 7]. Besides the coarse-grained classification of the idle and non-idle maneuvers, our classification algorithm allows us to classify wheelchair maneuvers into eight classes, i.e., idle state, linear acceleration, linear deceleration, linear constant speed, left turn, right turn, spot turn to left, and spot turn to right. The difference between the maneuvers of spot turns and maneuvers of left/right turns is that spot turns rotate the wheelchair without changing its location while left/right turns change the location of the wheelchair along an arc. Such fine-grained analysis can depict a more comprehensive picture of wheelchair users' activity and mobility levels.

This study is an extension of our previous research, in which we constructed a mobile- and cloud-computing based system to capture wheelchair maneuvering data [9]. The accelerometer and gyroscope in a smartphone were used to capture wheelchair maneuvering data, which were then transmitted to the cloud for the subsequent data processing and storage. With the proposed classification algorithm, it becomes feasible to effectively analyze noisy sensor data from wheelchair users' day-to-day maneuvers, and quantify their activity and mobility levels to measure their quality of life and health status.

II. METHODS

Unlike existing research, which extensively focuses on placing data loggers on the wheels of a wheelchair [1, 7, 8], our protocol only takes a single step, i.e., placing a smartphone on the armrest of a wheelchair to capture the maneuvering data. This is achieved by developing a smartphone app that controls the accelerometer and gyroscope in the smartphone [9]. Comparing with existing research, our approach largely simplifies the experimental setup. In addition, we also

This work was supported by the Oklahoma Center for the Advancement of Science and Technology (OCAST HR12-036).

J. Fu is with the University of Central Oklahoma, Edmond, OK 73034 USA (phone: 405-974-5704; e-mail: jfu@uco.edu).

T. Liu is with the University of Central Oklahoma, Edmond, OK 73034 USA.

M. Jones is with the University of Oklahoma Health Sciences Center, Oklahoma City, OK 73117 USA.

G. Qian is with the University of Central Oklahoma, Edmond, OK 73034 USA.

Y. K. Jan is with the University of Illinois at Urbana-Champaign, Champaign, IL 61820 USA.

employed the cloud computing technique to store and process wheelchair maneuvering data. The combination of mobile and cloud computing significantly improves the efficiency of data collection and storage.

A. Data Modeling and Noise Reduction

We model an instance of wheelchair maneuvering data as a 7-tuple vector:

$$\langle \alpha_x, \alpha_y, \alpha_z, g_p, g_r, g_y, t\rangle \qquad (1)$$

including accelerometer (α) and gyroscope (g) data in three axes, and a time-stamp (t) denoting when the instance is recorded. As shown in Figure 1, an accelerometer can capture accelerations in three axes (i.e., x, y, and z) and a gyroscope can record angular speed of pitch, roll, and yaw.

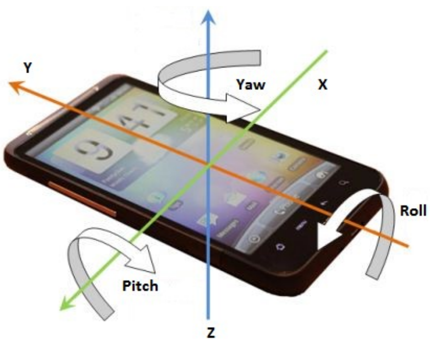

Figure 1: Three Axes of the Smartphone

As data captured by the accelerometer contains significant noises, we take two steps to reduce noises. First, we observed that the values of noises fluctuated within a certain range when the accelerometer was stationary. Hence, we average the sensor readings for the stationary period to obtain the averaged value Δ in axis d ($d = x, y,$ or z). Δ is then used to shift the entire data set in axis d, i.e., deduct Δ from each data instance. Second, to further reduce noises, we use the Kalman filter [10], which is a well-known algorithm for filtering noises and generating precise estimates of the underlying system states.

B. K-Nearest Neighbor

Our proposed algorithm utilizes the k-nearest neighbor (KNN) algorithm, which is a widely used classification algorithm due to its simplicity and effectiveness [11, 12]. In KNN, a data vector is classified into a class based on the majority vote of its k nearest neighbors. This approach fits in our study because we can adjust the parameter k to mitigate the impact of noises. To measure the affinity to the neighbors, we use the Euclidean distance:

$$\sqrt{\sum_{k=1}^{6}\left(S_i^k - T_j^k\right)^2} \qquad (2)$$

where S_i ($i = 1, 2, \ldots, m$) is a sample data vector and T_j ($j = 1, 2, \ldots, n$) is a testing data vector. Both of them are 6-dimensional vectors because there are 6 elements (of accelerometer and gyroscope) defined in Equation (1). The timestamp t in Equation (1) is not considered by KNN because it is not related to wheelchair maneuvering behaviors. Instead, t is used for the subsequent activity and mobility analysis. S_i^k denotes the k-th dimensional element in S_i and T_j^k denotes the k-th dimensional element in T_j.

C. Two-Step Classification Algorithm

The two-step classification algorithm classifies wheelchair maneuvering activities into eight commonly used classes, namely, idle state (i.e., stationary), linear acceleration, linear deceleration, linear constant speed, left turn, right turn, spot turn to left, and spot turn to right. This algorithm was designed based on the characteristics of wheelchair maneuvering data. As shown in Figure 2, the gyroscope data of yaw can help us easily distinguish the turning maneuvers (e.g., left turns and right turns) from the linear ones (e.g., linear acceleration and deceleration). The turning maneuvers have significantly larger absolute yaw values than their linear counterparts. Hence, our algorithm employs a two-step strategy to classify a maneuver. In the first step, it tries to determine whether the given maneuver is linear or turning. It then determines the exact maneuver in the second step. The advantage of this two-step strategy is that it can significantly reduce the chances of misclassifying linear maneuvers into turning ones and vice versa.

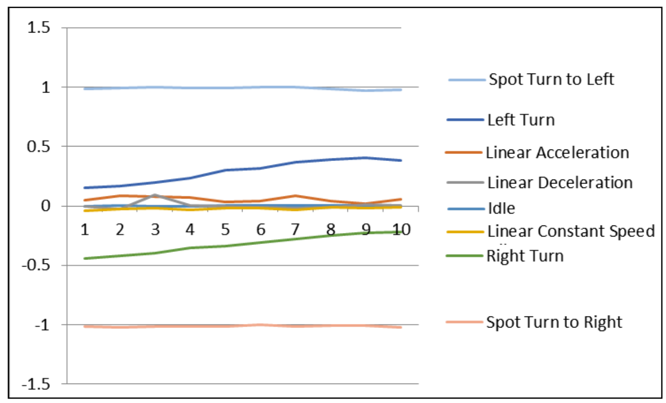

Figure 2: Yaw Gyroscope Data for Different Classes of Wheelchair Maneuvers

```
1.  Function Classify_Maneuver(d)
2.      Step 1:
3.          d1 ← Projec_Yaw(d)
4.          r ← KNN(d1)
5.      Step 2:
6.          if is-Linear(r) then
7.              d2 ← Project_Linear(d)
8.          else
9.              d2 ← Project_Turning(d)
10.     end if
11.     return KNN(d2)
12. End
```

Figure 3: Outline of the Two-Step Algorithm

Figure 3 outlines the proposed two-step classification algorithm. The input to the algorithm is a data segment d representing a wheelchair maneuver. The segment d consists of a sequence of data vectors in a format defined in Equation (1). In **Step 1**, the function *Project_Yaw* projects the input data segment d into d_1 (line 3 in Figure 3). Each vector in d_1 is a singleton $\langle g_y\rangle$, i.e., the yaw gyroscope data g_y. The reasons for using only yaw data are two folds. First, Figure 2 shows that data of yaw demonstrates distinctive patterns on linear and turning maneuvers. Second, this study focused on indoor settings, in which the ground was flat. Theoretically, the angular speeds of pitch and roll should be 0 in such an environment. Hence, our algorithm only considers yaw gyroscope data to determine the linearity of the maneuver by running the KNN (line 4).

In **Step 2**, the algorithm first checks whether the maneuver has been identified to be linear (line 6). If it is linear, the input data segment d is projected into the linear format (line 7), i.e., $\langle \alpha_y \rangle$. Here, α_y is the acceleration on axis y, which is the wheelchair's maneuvering direction. Accelerations on axis x are not considered because linear maneuvers do not have significant movements on axis x, which is perpendicular to the moving direction. Similarly, the angular speeds are not considered in liner maneuvers as well.

If the maneuver is non-linear (line 8), the input data segment d is projected into the turning format (line 9), i.e., $\langle \alpha_y, g_y \rangle$. Here, we employ acceleration data on axis y and yaw gyroscope data to precisely distinguish spot turns from regular left/right turns. This is because spot turns have larger absolute yaw speeds (as shown in Figure 2), while they demonstrate different patterns on accelerations of axis y from the regular left/right turns. Finally, our algorithm uses KNN to determine the exact wheelchair maneuver (line 11).

D. Experiment

We conducted an experiment inside an academic building in the University of Central Oklahoma. The smartphone we used was a Samsung Galaxy SII (GT-I9100) with Android OS 4.1 Jelly Bean. The built-in sensors, including an accelerometer and a gyroscope, were used to capture wheelchair maneuvering data. The sampling rate was set to "SENSOR_DELAY_UI" [9]. The wheelchair was an Invacare® power wheelchair.

We investigated four different K values for KNN used in our two-step algorithm, namely, K = 1, 3, 5, and 7. In KNN, each maneuver class was associated with 8 sample data vectors. Since the maneuvers were classified into 8 classes, the total number of sample data vectors was 64 in the sample space. When a testing data vector was provided, its class was determined by the majority of its K closest neighbors among the 64 vectors of sample data. Since raw sensor data contained significant noises, we did not use raw data in the experiments of classification. Instead, we conducted experiments on noise-reduced data processed with Kalman filter.

III. Results

Table I shows the experimental results. The columns include the value of K, the maneuver type, the number of data vectors that were tested, and the accuracy. Our two-step classification algorithm achieved very high accuracy in classifying wheelchair maneuvers. It perfectly classified the idle and spot turn maneuvers (i.e., 100%). Hence, our algorithm can precisely determine whether the wheelchair is moving. When K = 3, the algorithm achieved the highest averaged accuracy, i.e., 96.16%.

Table I: Experimental Results on the Two-Step Classification Algorithm

K	Maneuver Types	Num. of Vectors	Accuracy (%)
K=1	Idle	136	100.00%
	Linear acceleration	65	90.77%
	Linear deceleration	53	98.11%
	Linear constant speed	227	90.75%
	Left turn	78	88.46%
	Right turn	95	94.74%
	Spot turn to left	73	100.00%
	Spot turn to right	72	100.00%
	Average		**95.35%**
K=3	Idle	136	100.00%
	Linear acceleration	65	90.77%
	Linear deceleration	53	96.23%
	Linear constant speed	227	97.80%
	Left turn	78	89.74%
	Right turn	95	94.74%
	Spot turn to left	73	100.00%
	Spot turn to right	72	100.00%
	Average		**96.16%**
K=5	Idle	136	100.00%
	Linear acceleration	65	90.77%
	Linear deceleration	53	94.34%
	Linear constant speed	227	98.24%
	Left turn	78	89.74%
	Right turn	95	90.53%
	Spot turn to left	73	100.00%
	Spot turn to right	72	100.00%
	Average		**95.45%**
K=7	Idle	136	100.00%
	Linear acceleration	65	90.77%
	Linear deceleration	53	83.02%
	Linear constant speed	227	98.68%
	Left turn	78	89.74%
	Right turn	95	90.53%
	Spot turn to left	73	100.00%
	Spot turn to right	72	100.00%
	Average		**94.09%**

IV. Discussion

The literature demonstrates that existing research attempted to depict an increasingly more comprehensive picture about wheelchair users' activity and mobility levels. The information studied evolved from the subjective self-reported questionnaires [13] to more objective maneuvering time and distance [5, 6], and later to the measurement of bouts, which refer to segments of continuous wheelchair movement [2, 7]. Our fine-grained analysis on wheelchair maneuvers enables us to perform these analyses effectively. As our classification algorithm can accurately classify wheelchair maneuvers (see Table I), we can easily distinguish the maneuver of idle state from other maneuvers. Plus, time-stamps are included in all the data instances from the accelerometer and gyroscope. Hence, for the mobility level, we can measure the active hours by summing up the hours spent on all non-idle maneuvers. For the activity level, the maximum continuous maneuvering time can be determined by identifying the longest piece of data sequence sandwiched in between two consecutive idle states. Similarly, we can count the number of starts/stops and the number of bouts. By applying the trapezoidal rule or Simpson's rule [14] to accelerations, we can make more quantitative measurements on the activity level (such as the maximum continuous maneuvering distance), and the mobility level (such as the daily maneuvering distance, averaged speed, etc.).

In addition, the research area of indoor localization [15, 16] is related to our study. Indoor localization is especially important for wheelchair users because disability is often accompanied with impaired ability of spatial cognition [17]. However, existing indoor localization systems primarily target at healthy people. The localization is usually achieved through step detection and step length estimation [15, 16]. Unfortunately, wheelchair maneuvers do not possess such characteristics related to steps. The accelerations and decelerations of wheelchairs are instantaneous (usually less than 1 second). The subtle changes in maneuvers as well as the noises in maneuvering data compound the difficulty in determining the correct maneuvers. Our two-step classification algorithm overcame these challenges and achieved satisfactory precision in classifying wheelchair maneuvers as shown in Table I. As a result, our study may contribute to research on indoor localization as well.

A. *Study Limitation*

Our experimental environment is basically a 2-D setting as the floor is flat without up and down variations. In the next step, we will conduct experiments in more complex indoor environments.

V. Conclusion

In this study, we strived to characterize wheelchair maneuvering data to depict a comprehensive picture of wheelchair users' activity and mobility levels. As raw sensor data contained significant noises, we applied the well-known Kalman filter to reduce noises. Then, we developed a novel two-step classification algorithm to perform fine-grained analysis on wheelchair maneuvers. This algorithm was designed based on the characteristics of wheelchair maneuvering data, which demonstrated distinctive patterns on linear and turning maneuvers when the yaw angular speeds were considered. The first step of the algorithm tried to determine whether the given data segment was a linear or turning maneuver. Then, the second step of the algorithm determined the exact class of the maneuver. Experimental results showed that this two-step algorithm achieved high accuracy in classifying the wheelchair maneuvers even though noises still existed.

In the next step of our research, we will utilize the two-step classification algorithm to improve the precision of maneuvering distance measurements. First, we will employ this algorithm to identify wheelchair maneuvers. Then, we will calculate the maneuvering distance for each of the maneuvers with a suitable approach. The individual distances will be finally summed up to obtain the overall distance. This approach will largely mitigate the accumulated errors that existing approaches suffer. Therefore, our approaches will be able to depict a more accurate and comprehensive picture of wheelchair users' activity and mobility levels.

Acknowledgment

This work was supported by the Oklahoma Center for the Advancement of Science and Technology (OCAST HR12-036).

References

[1] M. L. Tolerico, D. Ding, R. A. Cooper, D. M. Spaeth, S. G. Fitzgerald, R. Cooper, *et al.*, "Assessing mobility characteristics and activity levels of manual wheelchair users," *J Rehabil Res Dev,* vol. 44, pp. 561-71, 2007.

[2] S. E. Sonenblum, S. Sprigle, F. H. Harris, and C. L. Maurer, "Characterization of power wheelchair use in the home and community," *Arch Phys Med Rehabil,* vol. 89, pp. 486-91, Mar 2008.

[3] F. Harris, S. Sprigle, S. E. Sonenblum, and C. L. Maurer, "The participation and activity measurement system: an example application among people who use wheeled mobility devices," *Disabil Rehabil Assist Technol,* vol. 5, pp. 48-57, Jan 2010.

[4] H. Wang, B. Salatin, G. G. Grindle, D. Ding, and R. A. Cooper, "Real-time model based electrical powered wheelchair control," *Med Eng Phys,* vol. 31, pp. 1244-54, Dec 2009.

[5] R. A. Cooper, T. Thorman, R. Cooper, M. J. Dvorznak, S. G. Fitzgerald, W. Ammer, *et al.*, "Driving characteristics of electric-powered wheelchair users: how far, fast, and often do people drive?," *Arch Phys Med Rehabil,* vol. 83, pp. 250-5, Feb 2002.

[6] R. A. Cooper, M. Tolerico, B. A. Kaminski, D. Spaeth, D. Ding, and R. Cooper, "Quantifying wheelchair activity of children: a pilot study," *Am J Phys Med Rehabil,* vol. 87, pp. 977-83, Dec 2008.

[7] S. E. Sonenblum, S. Sprigle, J. Caspall, and R. Lopez, "Validation of an accelerometer-based method to measure the use of manual wheelchairs," *Med Eng Phys,* vol. 34, pp. 781-6, Jul 2012.

[8] E. H. Coulter, P. M. Dall, L. Rochester, J. P. Hasler, and M. H. Granat, "Development and validation of a physical activity monitor for use on a wheelchair," *Spinal Cord,* vol. 49, pp. 445-50, Mar 2011.

[9] J. Fu, W. Hao, T. White, Y. Yan, M. Jones, and Y. K. Jan, "Capturing and analyzing wheelchair maneuvering patterns with mobile cloud computing," *Conf Proc IEEE Eng Med Biol Soc,* vol. 2013, pp. 2419-22, 2013, PMID: 24110214.

[10] G. Welch and G. Bishop. (1995). *An Introduction to the Kalman Filter*. Available: http://www.cs.unc.edu/~welch/kalman/kalmanIntro.html

[11] A. Dhurandhar and A. Dobra, "Probabilistic characterization of nearest neighbor classifier," *International Journal of Machine Learning and Cybernetics,* vol. 4, pp. 259-272, 2013/08/01 2013.

[12] W. Shang, H. Huang, H. Zhu, Y. Lin, Z. Wang, and Y. Qu, "An Improved kNN Algorithm – Fuzzy kNN," in *Computational Intelligence and Security*. vol. 3801, Y. Hao, J. Liu, Y. Wang, Y.-m. Cheung, H. Yin, L. Jiao*, et al.*, Eds., ed: Springer Berlin Heidelberg, 2005, pp. 741-746.

[13] C. E. Tudor-Locke and A. M. Myers, "Challenges and opportunities for measuring physical activity in sedentary adults," *Sports Med,* vol. 31, pp. 91-100, Feb 2001.

[14] R. Tallarida and R. Murray, "Area under a Curve: Trapezoidal and Simpson's Rules," in *Manual of Pharmacologic Calculations*, ed: Springer New York, 1987, pp. 77-81.

[15] M. Research. *Mobile Indoor Localization*. Available: http://research.microsoft.com/en-us/projects/indoorloc/

[16] J. A. B. Link, P. Smith, N. Viol, and K. Wehrle, "FootPath: Accurate map-based indoor navigation using smartphones," in *Indoor Positioning and Indoor Navigation (IPIN), 2011 International Conference on*, 2011, pp. 1-8.

[17] L. Song, W. Che, W. Min-wei, Y. Murakami, and K. Matsumoto, "Impairment of the spatial learning and memory induced by learned helplessness and chronic mild stress," *Pharmacology Biochemistry and Behavior,* vol. 83, pp. 186-193, 2006.