A FRAMEWORK TO ENHANCE ASSISTIVE TECHNOLOGY BASED MOBILITY TRACKING IN INDIVIDUALS WITH SPINAL CORD INJURY

Amir Mohammad Amiri, Noor Shoaib, Shivayogi V. Hiremath

Department of Physical Therapy, College of Public Health,
Temple University, Philadelphia, PA 19140, USA
Shiv.Hiremath@temple.edu

ABSTRACT

Assistive technologies such as wheelchairs, canes, and walkers have significantly improved the mobility, function, and quality of life for individuals with spinal cord injury (SCI). In this article, we propose a framework which combines machine learning algorithms with wearable sensors to capture and track mobility in individuals with SCI. Pilot testing in two individuals without SCI indicated that four to seven features obtained from sensors worn on the body or placed on the assistive technology could successfully detect mobility and mobility modes. The classification accuracy for Naïve Bayes and Decision Tree algorithms to detect mobility from non-mobility activity varied from 87.4% to 97.6%. The classification accuracy for detecting six mobility modes within mobility ranged from 88.5% to 90.6%. The proposed framework has the potential to assist researchers and clinicians to study complex mobility patterns of individuals with SCI and provide adaptive rehabilitation and physical activity interventions in the community.

Index Terms— Assistive technology, sensors, machine learning, activity monitoring, spinal cord injury

1. INTRODUCTION

The National Spinal Cord Injury Statistical Center estimated that approximately 300,000 people with spinal cord injury (SCI) live in the United States of America in the year 2016, with 17,000 new cases each year [1]. An SCI can lead to loss of strength, sensation, and function which in turn may lead to reduced mobility such as the inability to stand and walk [2-4]. Restoration of mobility function in individuals with SCI can have a significant impact on the health, quality of life, and social participation [4-6]. To address this need, a rehabilitation team including clinicians, the individual with SCI, and their family members assess the functional limitations and the community goals of the individual with SCI to provide an intensive inpatient and outpatient rehabilitation treatment.

In recent years' assistive technologies such as wheelchairs, canes, and walkers have significantly improved the mobility, function, and quality of life for individuals with SCI. Depending on the person's function and the level of SCI a clinician may prescribe various forms of assistive technologies for mobility (Figure 1). Use of mobility aids or assistive technologies combined with a person's function (or lack of) results in changes to the biomechanical pattern of walking or mobility. Currently, most gait research has focused on how to assist people towards "normal" walking, defined as walking without the use of assistive technologies, but the proposed framework recognizes the importance and normality of assistive devices for individuals with SCI. This framework fills an important gap in understanding and improving mobility modes of individuals with SCI who use assistive technology.

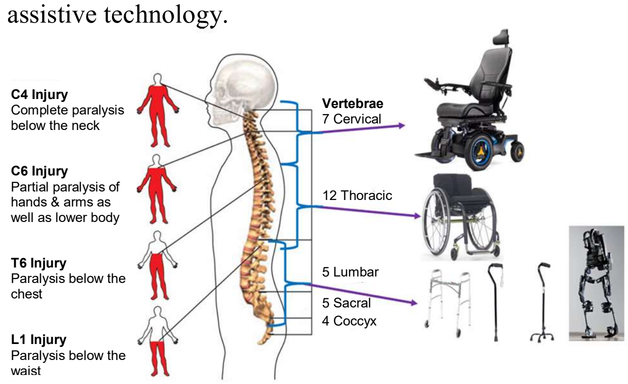

Figure 1: A person-specific function will influence the choice of assistive technology for various mobility modes.

2. RELATION TO PRIOR WORK

Sensor-based activity monitors have been used to track wheelchair movement [7-11], arm or wrist movements [12-15], and physiological changes [10, 13] for quantifying physical activities among individuals who use wheelchairs. Garcia-Masso et al. and Nightingale et al. [14, 15] indicated that the energy expenditure estimated by the activity counts from Actigraph GT3X worn on the wrist was correlated with energy expenditure (housework activities, arm-ergometry, and propulsion: r=0.86 [14], propulsion and deskwork: r=0.93 [15]). Hiremath et al. used SenseWear, a multi-sensor based activity monitor, to detect and classify four physical activities including resting, wheelchair propulsion, arm-ergometry, and deskwork in individuals with SCI [16]. Additionally, Hiremath et al. developed a Physical Activity Monitor Systems that combined information from a wrist-worn accelerometer with a wheel rotation monitor to detect and classify seven wheelchair related physical activities (accuracy: 89%) [17]. The classification algorithms utilized included Naïve Bayes, Support Vector Machine and Decision Trees. In another study, Bowden et al. focused on step count using an accelerometer placed on the leg for individuals with SCI (accuracy: 97% for 6 min and 10 m walk tests) [18].

Research in other populations with mobility impairments include sensors worn on ankles [19, 20], shank [21] and waist [22] towards detecting and quantifying mobility [23] in individuals with stroke. Dobkin et al. evaluated a tri-axial accelerometer on the ankle of individuals with hemiparetic stroke [19]. Naïve Bayes classifier and a heuristic algorithm were used to detect walking and estimate walking speed, respectively. The walking speed was estimated based on a correlation between the individual walking a fixed distance of 50 feet and the algorithm detecting the walking (r=0.98). Xu et al. developed a hierarchical classification system that combined Naïve Bayes and dynamic time warping algorithms to detect walking in 6 individuals with stroke [19].

A major limitation of the current research is that the existing research has focused on individuals who use specific types of assistive technologies such as manual wheelchairs or walking. In this article, we propose a framework that can enhance mobility tracking by detecting complex mobility modes (using a wheelchair, walking with a cane or a walker, or other mobility activity) influenced by functional limitations and assistive technology usage.

3. A FRAMEWORK TO ENHANCE MOBILITY TRACKING

We propose a framework which uses a combination of machine learning models and wearable sensors to capture and track assistive technology-based mobility and function in individuals with SCI (Figure 2). The machine learning models will consist of personalized algorithms that can utilize modified human biomechanical movement pattern captured by sensors to predict mobility and mobility modes. The modified human biomechanical movement pattern is a result of interaction between mobility influenced by person-specific function and mobility modes due to assistive technology used for mobility (Figure 3).

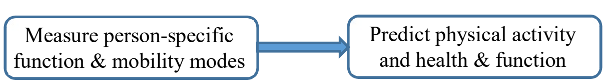

Figure 2: A framework consisting of measuring and predicting physical activity and health and function.

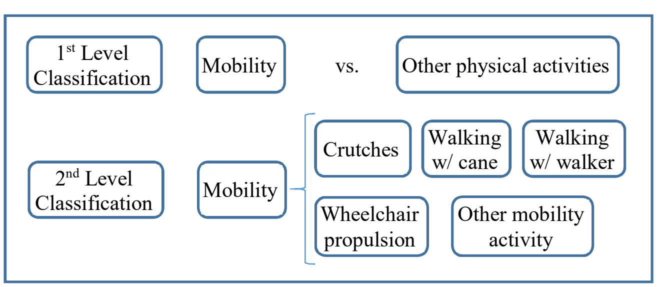

Figure 3: Machine learning algorithms used to detect various mobility modes.

Personalizing the activity classifiers will involve two steps (Figure 3). First, we will detect mobility based activities from the rest of the physical activities [17, 20, 22]. Second, we will identify various types of mobility modes in individuals with SCI influenced by functional limitations and assistive technology usage within the detected mobility activity. Detection and quantification of different mobility modes will transform future research studies that assess rehabilitation outcomes in individuals with SCI in the community.

3.1. Placement of Sensors

Sensor placement on the individual and or the assistive technology [17, 24] can play a significant role in obtaining features that reflect biomechanical data of mobility and mobility modes (Figure 4). Factors that may affect sensor placement include wearability and burden to the individuals with paralysis. The sensor orientation and placement at certain extremities such as wrist versus ankle may provide more information for certain activities (wheelchair propulsion vs. walking). Sensor placement on the assistive technology may provide a unique perspective on usage and the movement information as it has limited degrees of freedom compared to the extremities.

Figure 4: An investigator using various types of mobility aids. Red circles highlight the SenseWear armbands.

3.2. Developing Feature Data

Statistical measures such as time and frequency domain features [17, 25, 26] will need to be extracted to distinguish between various types of activities and mobility modes related to use or non-use of assistive technology [17]. The time domain features such as mean, mean absolute deviation, and peaks are simple to extract and can be used to classify mobility versus other physical activities (activities that are considerably different). The frequency domain features such as total power between a band of frequencies, energy, and entropy provide classification models the capability to differentiate walking, walking with assistive technology, or wheelchair propulsion (activities based on the fundamental frequency of human movement). Real-time extraction of frequency domain features on smartphones or mobile health-based platforms may require higher computation capacity than time domain features. Based on our previous work in individuals with SCI [16, 17] we have found that extracting features based on 10s and 1 min window size have resulted in successful classification of mobility and physical activities. Collecting acceleration data from sensors in a format that is close to the raw format (m/s^2) compared to activity counts (used by some sensor-based platforms) will allow researchers to develop various types of feature data post-data collection. Based on the sensor-based platforms used to collect data the captured human movement data may vary in range (±2g or ±4g: g – acceleration due to gravity $9.8 m/s^2$) and sampling frequency (10Hz to 110Hz: Hz – samples per second).

3.3. Machine Learning Algorithms

Following feature extraction, machine learning algorithms such as hierarchical models need to be evaluated to detect complex mobility modes and assistive technology usage. The development of hierarchical models is a two-step process of using algorithms such as Support Vector Machines, Naïve Bayes, or Decision Trees to detect mobility from other physical activities. Then using a joint classification algorithm such as Dynamic Time Warping (DTW) [27] combined with Naïve Bayes to detect a mobility mode within the larger activity of mobility. The DTW algorithm will allow for personalizing the algorithms to specific waveforms from wearable sensors collected during patterns of modified gait or mobility. Personalizing the algorithms will allow for detecting multiple mobility modes in an individual over a day, which in turn will quantify the duration of time a person performs a specific activity using assistive technologies.

Personalization of the algorithms may be necessary to improve detection of mobility and other physical activities due to the interaction of an individual's function and assistive technology. Personalization of algorithms and choice of features to detect activities in an individual will increase the classification accuracy. However, personalization may also lead to overfitting of the models. One approach to limit overfitting is to use classification algorithms that can include or are not sensitive to slight variations in feature data and use a limited number of features. Previous research by our group has used five to seven features to perform classification in 45 individuals with SCI.

3.4. Mobility Assessment Analysis

Various assessment metrics such as precision, recall, F-score, and accuracy of classification algorithms should be used to assess mobility tracking [28]. Data collected should be split into training and testing datasets to evaluate both within-subject and between-subject classification performance. Within-subject classification is necessary when the features and classification algorithms developed and evaluated are personalized. For example, 10-fold-stratified cross-validation (CV) [29] and leave-one-session-out CV should be assessed for within-subject algorithm evaluations. Between-subject classification is appropriate when the same set of features are used to develop classification algorithms on a group of individuals with SCI who use specific assistive technologies resulting in a similar biomechanical movement. 10-fold and leave-one-subject-out CV should assess the performance of the algorithms.

4. PILOT EVALUATION OF THE FRAMEWORK

We evaluated the framework in two investigators without SCI. The pilot evaluation included collecting data from six SenseWear armbands (BodyMedia Inc.) for five commonly used assistive technologies by individuals with paralysis. The individuals wore four armbands on each of their ankles and wrists. The remaining armbands were attached to the assistive devices. The assistive devices included a wheelchair, crutches, walker, and two types of canes (quad cane and regular single tip). The armbands monitored 3-axis acceleration in m/s^2 at a 32Hz sampling rate. Each participant traveled 15m with all of the assistive devices while simulating walking or wheelchair propulsion similar to an individual with SCI. Each investigator performed multiple trials of data collection. InnerView software was used to retrieve the data from the armbands. Statistical measures such as time and frequency domain features were calculated based on the data collected from the armbands [16, 17]. The features were extracted using custom programs written in MATLAB (version 2016b) for a 10s window size.

4.1. Biomechanical Patterns of Assisted Mobility

Figure 5 shows various patterns of resultant acceleration (sampled at 32Hz) for simulated mobility patterns with assistive technology for individuals with SCI. The patterns also indicate the challenge of capturing and assessing the complex mobility modes performed by individuals with SCI. The acceleration patterns for some of the sensors and mobility modes are small. But the feature data obtained from these sensors combined with personalized classification algorithms allowed us to distinguish them from other physical activities such as standing idle, sitting, or other non-mobility based activities.

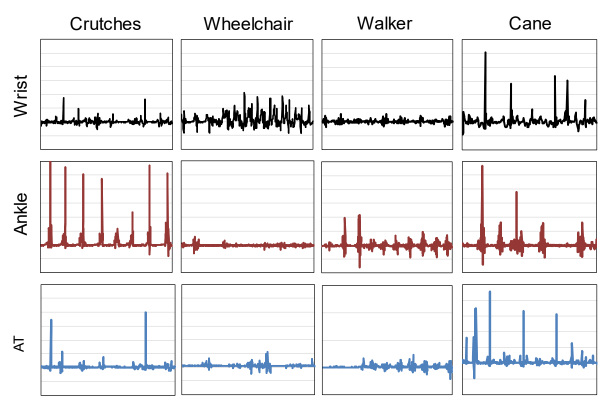

Figure 5: Resultant acceleration from sensors placed on ankle, wrist, and assistive technology (AT) for various mobility modes. X and Y axes represent samples and acceleration (0-4 m/s^2), respectively.

4.2. Classification of Mobility and Mobility Modes

Feature data from the tri-axial accelerometers placed on the person and assistive technology were used to classify mobility from non-mobility activities. The classification accuracy using the Naïve Bayes and Decision Tree algorithms for four features varied from 87.4% to 97.6% for individual and combined devices (armbands on the person and the assistive technology). Multiple evaluations including 10-fold CV and 50%-CV (50% for training and 50% for testing) were performed to assess within-subject classification accuracy.

Furthermore, within the mobility based activities, the mobility modes for two participants were classified using seven features with an accuracy ranging from 88.5% to 90.6%. A high percentage of classification within mobility based activities (six classes) compared to just detecting mobility from non-mobility based activities was due to the higher number of features used for classification. Also, certain non-mobility based activities had intermittent mobility bouts of short duration (about 10s).

DTW algorithm was used to detect biomechanical variations of mobility with multiple mobility modes. Figure 6 shows the sensor pattern for a wrist-worn sensor during two types of mobility-based activities. For example, DTW was used to detect wheelchair propulsion from cane use. Figure 7 shows the plot of distance measure obtained by the DTW algorithm for an automatically chosen wheelchair propulsion template with walking while using a cane.

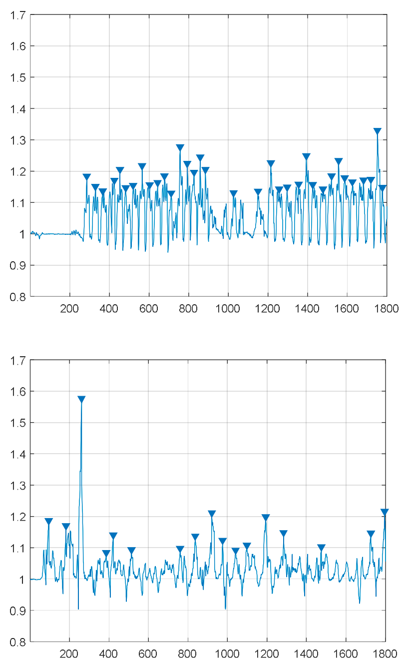

Figure 6: Resultant acceleration from a wrist sensor for wheelchair propulsion (top) and cane use (bottom). X and Y axes are samples and acceleration in m/s^2, respectively.

5. DISCUSSION

Pilot evaluation of the framework indicated that feature data obtained from armbands worn on the body or placed on the assistive technology could detect mobility and mobility modes in individuals using assistive technology for

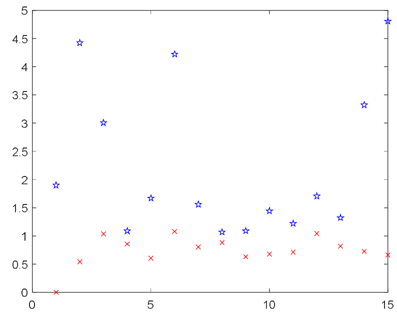

Figure 7: DTW for each propulsion cycle (red x) or walk with a cane (blue ☆). Y axis represents distance in m/s^2.

locomotion. In addition, algorithms such as DTW can be used to detect biomechanical patterns for various mobility modes (canes, crutches, and wheelchairs). Further evaluation of this framework is necessary for a large number of individuals who have a varied level of injury and have a complete or an incomplete SCI. A key finding from this study was that a sensor on the assistive technology improved overall classification accuracy as it provided feature based information that was complementary to the sensor worn on the wrist or the ankle of a person. The improvement in classification accuracy is similar to our prior research in individuals with SCI where two sensors were used to track upper arm and wheelchair movement, respectively [17].

The proposed framework has the potential to assist researchers to study complex mobility in the community and allow clinicians to transition individuals with SCI in the community from one mobility mode (wheelchair or a walker) to another (walker, robotic exoskeleton, cane or no assistive technology). Improved mobility can lead to better treatment outcomes and quality of life [4]. Furthermore, complex mobility patterns, detected by personalized algorithms, can be used to adaptively provide rehabilitation and physical activity interventions in the community.

Future work should also assess other types of machine learning algorithms such as linear-chain conditional random field models that can detect and capture activities that have a certain sequence or possible sequence of activities. Linear-chain conditional random field models were designed and used for structured prediction problems in natural language processing [30], recently linear-chain conditional random field models have been used to detect behaviors or activities [31]. Future research should also evaluate this framework in individuals with stroke and traumatic brain injury who may have hemiparesis or hemiplegia and use assistive technology for mobility.

6. ACKNOWLEDGMENT

The work is supported by the Personal Health Informatics & Rehabilitation Engineering laboratory, Department of Physical Therapy, Temple University, and the Craig H. Neilsen Foundation (Project# 382252).

6. REFERENCES

[1] National Spinal Cord Injury Statistical Center. (2016, August 9). *Spinal cord injury (SCI) facts and figures at a glance*. Available: https://www.nscisc.uab.edu/Public/Facts%202016.pdf

[2] J. W. McDonald and C. Sadowsky, "Spinal-cord injury," *The Lancet,* vol. 359, pp. 417-425, 2002.

[3] N. M. Crewe and J. S. Krause, "Spinal cord injury," *Medical, psychosocial and vocational aspects of disability. Athens: Elliott and Fitzpatrick,* pp. 289-304, 2009.

[4] S. V. Hiremath, N. S. Hogaboom, M. R. Roscher, L. A. Worobey, M. L. Oyster, and M. L. Boninger, "Longitudinal prediction of quality of life scores and locomotion in individuals with traumatic spinal cord injury," *Archives of physical medicine and rehabilitation,* In Press.

[5] L. A. Simpson, J. J. Eng, J. T. Hsieh, Wolfe, and D. L. the Spinal Cord Injury Rehabilitation Evidence Research Team, "The health and life priorities of individuals with spinal cord injury: a systematic review," *Journal of neurotrauma,* vol. 29, pp. 1548-1555, 2012.

[6] P. A. Jayaraman and W. Z. Rymer, "Exoskeletons for Rehabilitation and Personal Mobility: Creating Clinical Evidence," in *Wearable Robotics: Challenges and Trends*, ed: Springer, 2017, pp. 21-24.

[7] 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," *Journal of Rehabilitation R and D,* vol. 44, pp. 561-72, 2007.

[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," *Journal of Spinal Cord,* vol. 49, pp. 445-450, 2011.

[9] S. E. Sonenblum, S. Sprigle, J. Caspall, and R. Lopez, "Validation of an accelerometer-based method to measure the use of manual wheelchairs," *Medical Engineering and Physics,* vol. 34, pp. 781-86, 2012.

[10] S. A. Conger, S. N. Scott, and D. R. Bassett, "Predicting energy expenditure through hand rim propulsion power output in individuals who use wheelchairs," *British Journal of Sports Medicine,* vol. 48, pp. 1048-1053, 2014.

[11] S. V. Hiremath, D. Ding, and R. A. Cooper, "Development and evaluation of a gyroscope based wheel rotation monitor for manual wheelchair users.," *Spinal Cord Medicine,* vol. 36, pp. 347-356, 2013.

[12] K. Kiuchi, T. Inayama, Y. Muraoka, S. Ikemoto, O. Uemura, and K. Mizuno, "Preliminary study for the assessment of physical activity using a triaxial accelerometer with a gyro sensor on the upper limbs of subjects with paraplegia driving a wheelchair on a treadmill," *Spinal Cord,* vol. 52, pp. 556-563, 2014.

[13] S. V. Hiremath, D. Ding, J. Farringdon, and R. A. Cooper, "Predicting energy expenditure of manual wheelchair users with spinal cord injury using a multi-sensor based activity monitor," *Archives of Physical Medicine and Rehabilitation,* vol. 93, pp. 1937-1943, 2012.

[14] X. García-Massó, P. Serra-Añó, L. García-Raffi, E. Sánchez-Pérez, J. López-Pascual, and L. Gonzalez, "Validation of the use of Actigraph GT3X accelerometers to estimate energy expenditure in full time manual wheelchair users with spinal cord injury," *Spinal Cord,* vol. 51, pp. 898-903, 2013.

[15] T. E. Nightingale, J.-P. Walhin, D. Thompson, and J. L. Bilzon, "Predicting Physical Activity Energy Expenditure in Manual Wheelchair Users," *Medicine and Science in Sports and Exercise,* vol. 46, pp. 1849-58, 2014.

[16] S. Hiremath, D. Ding, J. Farringdon, N. Vyas, and R. Cooper, "Physical activity classification utilizing SenseWear activity monitor in manual wheelchair users with spinal cord injury," *Spinal cord,* vol. 51, pp. 705-709, 2013.

[17] S. V. Hiremath, S. S. Intille, A. Kelleher, R. A. Cooper, and D. Ding, "Detection of physical activities using a physical activity monitor system for wheelchair users," *Medical Engineering and Physics,* vol. 37, pp. 68-76, 2015.

[18] M. G. Bowden and A. L. Behrman, "Step Activity Monitor: accuracy and test-retest reliability in persons with incomplete spinal cord injury," *Journal of rehabilitation research and development,* vol. 44, p. 355, 2007.

[19] B. H. Dobkin, X. Xu, M. Batalin, S. Thomas, and W. Kaiser, "Reliability and validity of bilateral ankle accelerometer algorithms for activity recognition and walking speed after stroke," *Stroke,* vol. 42, pp. 2246-2250, 2011.

[20] X. Xu, M. A. Batalin, W. J. Kaiser, and B. Dobkin, "Robust hierarchical system for classification of complex human mobility characteristics in the presence of neurological disorders," in *2011 Conference on Body Sensor Networks*, 2011, pp. 65-70.

[21] S. Yang, J.-T. Zhang, A. C. Novak, B. Brouwer, and Q. Li, "Estimation of spatio-temporal parameters for post-stroke hemiparetic gait using inertial sensors," *Gait & posture,* vol. 37, pp. 354-358, 2013.

[22] N. Capela, E. Lemaire, N. Baddour, M. Rudolf, N. Goljar, and H. Burger, "Evaluation of a smartphone human activity recognition application with able-bodied and stroke participants," *Journal of neuroengineering and rehabilitation,* vol. 13, p. 1, 2016.

[23] H. Zheng, N. D. Black, and N. D. Harris, "Position-sensing technologies for movement analysis in stroke rehabilitation," *Medical and biological engineering and computing,* vol. 43, pp. 413-420, 2005.

[24] S. V. Hiremath, S. S. Intille, A. Kelleher, R. A. Cooper, and D. Ding, "Estimation of Energy Expenditure for Wheelchair Users Using a Physical Activity Monitoring System," *Archives of physical medicine and rehabilitation,* vol. 97, pp. 1146-1153. e1, 2016.

[25] S. V. Hiremath, S. S. Intille, A. Kelleher, R. A. Cooper, and D. Ding, "Estimation of energy expenditure for wheelchair users using a Physical Activity Monitoring System," *Archives of Physical Medicine and Rehabilitation,* 2015.

[26] S. S. Intille, F. Albinali, S. Mota, B. Kuris, P. Botana, and W. L. Haskell, "Design of a wearable physical activity monitoring system using mobile phones and accelerometers," in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference*, 2010, pp. 3636-3639.

[27] D. J. Berndt and J. Clifford, "Using dynamic time warping to find patterns in time series," in *KDD workshop*, 1994, pp. 359-370.

[28] I. H. Witten, E. Frank, M. A. Hall, and C. J. Pal, *Data Mining: Practical machine learning tools and techniques*: Morgan Kaufmann, 2016.

[29] R. J. Adams, A. Parate, and B. M. Marlin, "Hierarchical Span-Based Conditional Random Fields for Labeling and Segmenting Events in Wearable Sensor Data Streams," in *Proceedings of The 33rd International Conference on Machine Learning*, 2016, pp. 334-343.

[30] J. Lafferty, A. McCallum, and F. Pereira, "Conditional random fields: Probabilistic models for segmenting and labeling sequence data," in *Proceedings of the eighteenth international conference on machine learning, ICML*, 2001, pp. 282-289.

[31] E. Kim, S. Helal, and D. Cook, "Human activity recognition and pattern discovery," *IEEE Pervasive Computing,* vol. 9, pp. 48-53, 2010.