A Framework to Enhance Assistive Technology-based Mobility Tracking in Individuals with Spinal Cord Injury

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Introduction

- Approximately 300,000 people with spinal cord injury (SCI) live in the United States of America, with 17,000 new cases each year [1].
- 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, 3].
- Restoration of mobility function in individuals with SCI can have a significant impact on the health, quality of life, and social participation [3, 4].

1. National Spinal Cord Injury Statistical Center, 2016; 2. MacDonald *et al*. 2002; 3. Hiremath *et al*. 2017; 4. Jayaraman *et al*. 2017

Introduction

- 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.

Variation in Mobility

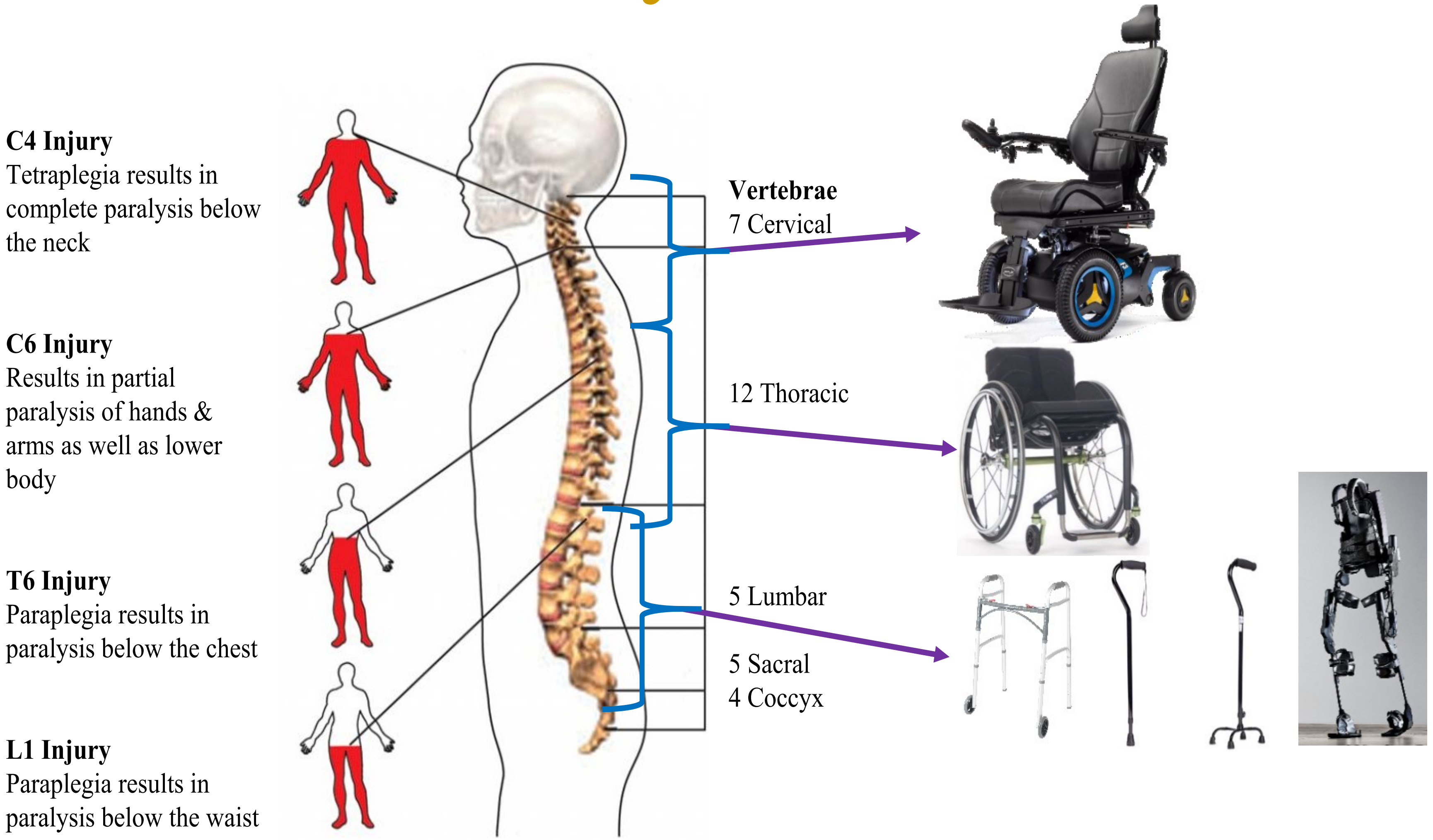

Figure 1: A person-specific function will influence the choice of assistive technology for various mobility modes.

Objective

- Currently, most gait research has focused on how to assist people towards "normal" walking, defined as walking without the use of assistive technologies.

- The proposed framework recognizes the importance and normality of assistive devices for individuals with SCI.

Prior Work

- Sensor-based activity monitors have been used to track wheelchair movement, arm movement, and physiological changes for quantifying physical activities in individuals with SCI [5].

- Research in other populations with mobility impairments include sensors worn on ankles, shank and waist towards detecting and quantifying mobility in individuals with stroke [6].

5. Hiremath *et al*. 2013; 6. Dobkin *et al*. 201

Prior Work

- 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.

Framework

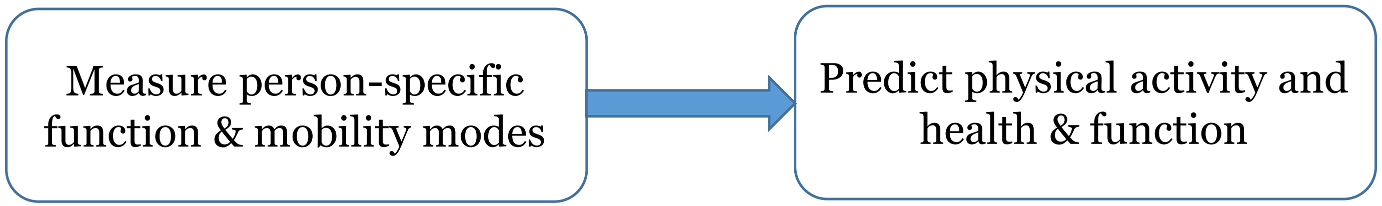

Figure 2: A framework consisting of measuring and predicting physical activity and health and function.

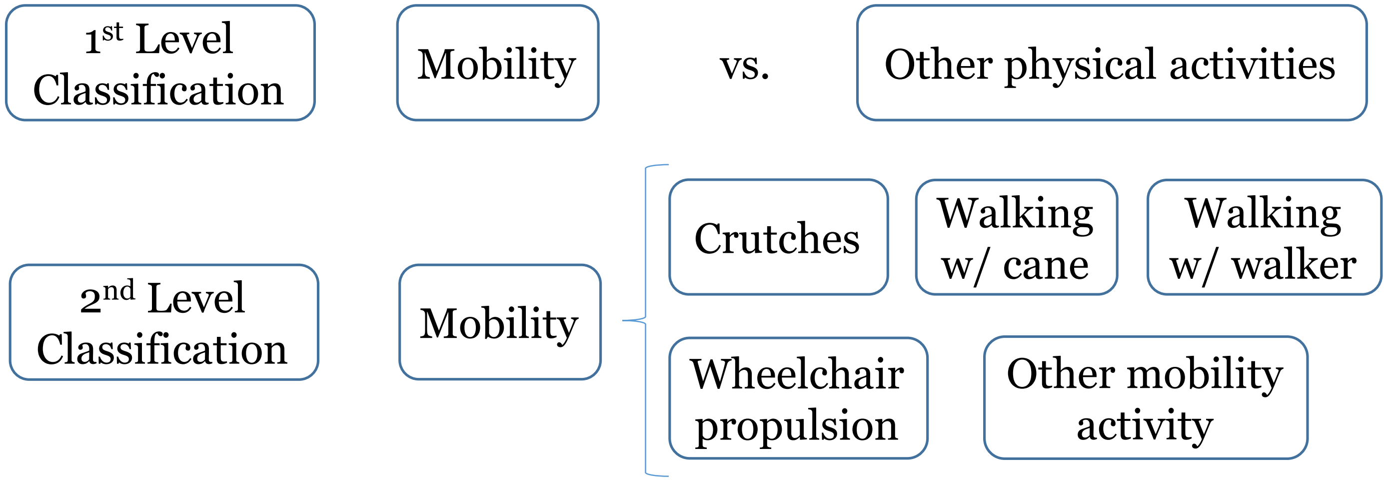

Figure 3: Machine learning algorithms used to detect various mobility modes.

Sensor Placement

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

Feature Data

- Statistical measures such as time and frequency domain features were extracted to distinguish between various types of activities and mobility modes.

- Time domain features (mobility vs. other physical activities)
  - Mean, mean absolute deviation and peaks

- Frequency domain features (classify within mobility)
  - Total power between a band of frequencies, energy, and entropy

Machine Learning Algorithms

- Hierarchical models is a two-step process
  - Support Vector Machines, Naïve Bayes, or Decision Trees to detect mobility from other physical activities
  - Use a joint classification algorithm such as Dynamic Time Warping (DTW) combined with Naïve Bayes to detect a mobility mode within the larger activity of mobility [7].

- DTW algorithm will allow for personalizing the algorithms to specific waveforms from wearable sensors collected during patterns of modified gait or mobility.

7. Berndt and Clifford 1994

Pilot Evaluation of Framework

- Two investigators without SCI traveled 15m with five assistive devices while simulating walking or wheelchair propulsion similar to an individual with SCI
  - Wheelchair, crutches, walker, quad cane and single tip cane.

- Data was collected from SenseWear armbands for five commonly used assistive technologies
  - Individuals wore four armbands on each of their ankles and wrists
  - Two armbands were attached to the assistive devices.

Biomechanical Patterns of Assisted Mobility

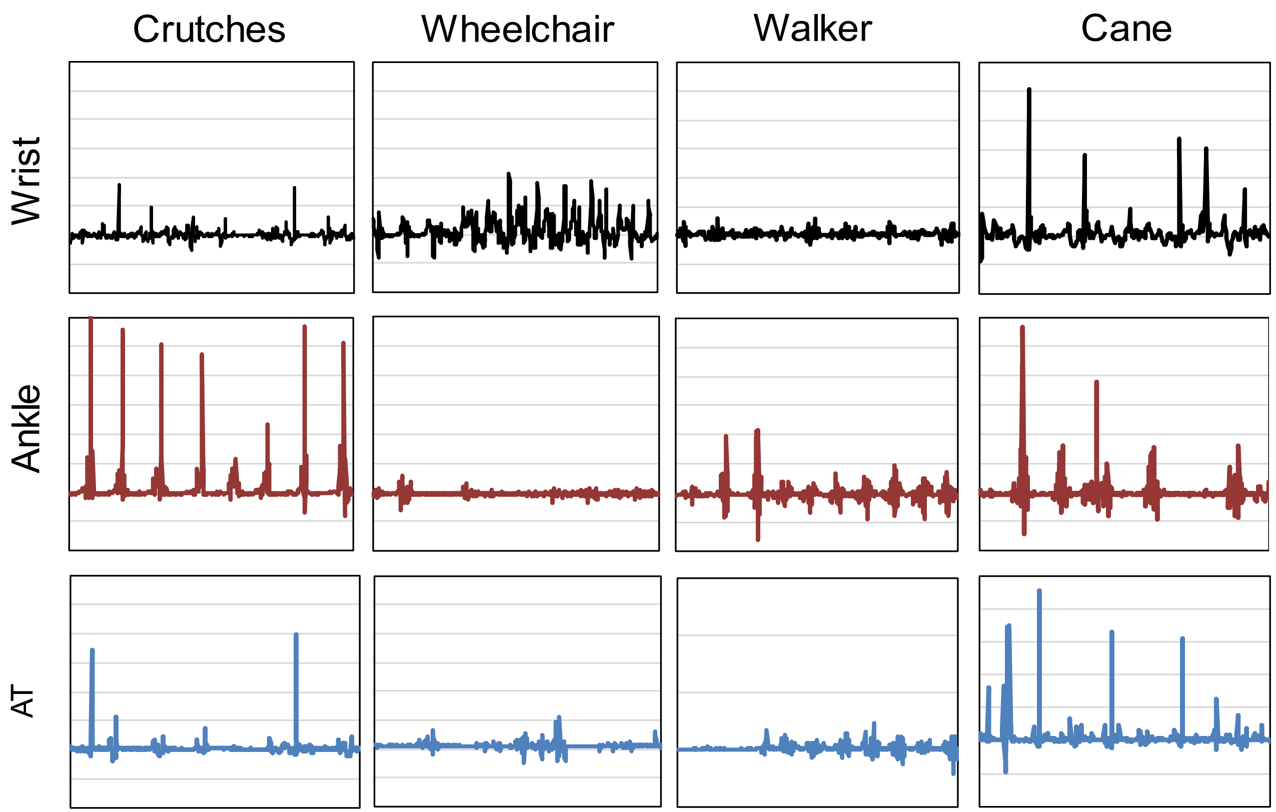

Figure 5: Resultant acceleration from sensors placed on ankle, wrist, and assistive technology (AT) for various mobility modes. X and Y axes represent samples and acceleration (0-4 m/s^2), respectively.

Classification

Mobility

- Classification accuracy using Naïve Bayes and Decision Tree algorithms for four features varied from 87.4% to 97.6% for individual and combined devices.
- Multiple evaluations including 10-fold CV and 50%-CV were performed to assess within-subject classification accuracy.

Mobility Modes

- Seven features classified six mobility-based activities with an accuracy ranging from 88.5% to 90.6%.

DTW

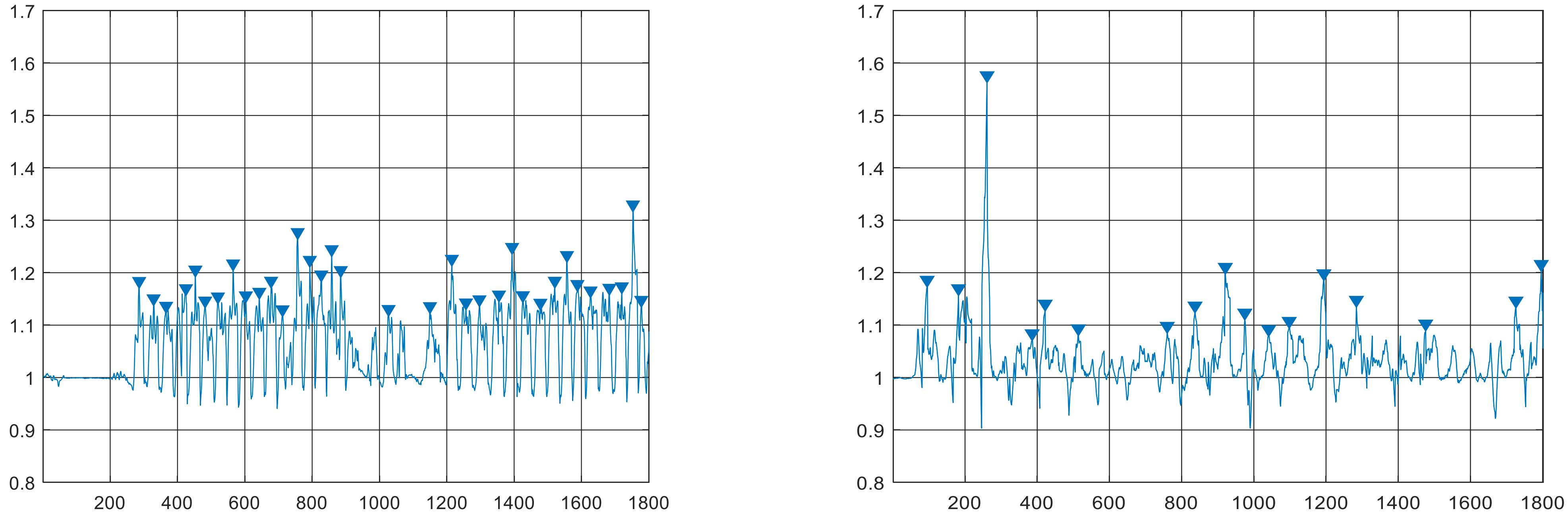

Figure 6: Resultant acceleration from a wrist sensor for wheelchair propulsion (left) and cane use (right). X and Y axes are samples and acceleration in m/s^2, respectively.

DTW

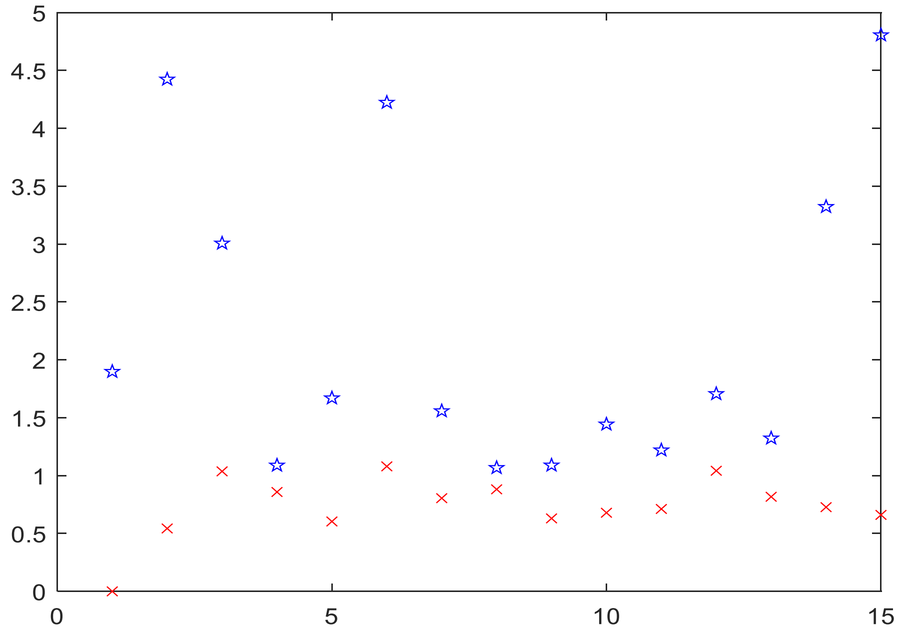

Figure 7: DTW for each propulsion cycle (red x) or walk with a cane (blue ⋆). Y axis represents distance in m/s^2.

Discussion

- Feature data obtained from armbands worn on the body or placed on the assistive technology could detect mobility and mobility modes in individuals during locomotion.

- 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 in large number of individuals who have a varied level of injury and have a complete or an incomplete SCI.

- Sensor on the assistive technology improved overall classification accuracy as it provided complementary information to wrist or the ankle movement.

Discussion

- The proposed framework has the potential to assist researchers to study complex mobility in the community and allow clinicians to transition individuals with SCI from one mobility mode to another.

- Improved mobility can lead to better treatment outcomes and quality of life [3].

- Complex mobility patterns, detected by personalized algorithms, can be used to adaptively provide rehabilitation and physical activity interventions in the community.

3. Hiremath *et al.* 2017

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