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14. ABSTRACT
Falling is a common problem for lower limb amputees, which can lead to reduced physical and emotional health. The overall aims of this project are to: 1) establish a baseline fall detection algorithm derived from simulated falls in a laboratory setting, and 2) utilize and refine the initial laboratory-based algorithm to provide detection of fall events during activities of daily living in real-world environments. To achieve these aims we will perform two human subject experiments. The first experiment will use 30 non-amputee and 5 lower limb amputee individuals to simulate falls in a laboratory setting while wearing the sensor. However, due to the COVID-19 pandemic, we were delayed in starting our data collection. However, in January 2021 we were given approval to start data collection and we have completed 30 non-amputee and 4 lower limb amputee individuals to date. We are currently refining our baseline fall detection algorithm and will begin implementing the algorithm in the sensor the amputees will wear in our second experiment where we will recruit 40 lower limb amputees to wear the sensor in the real-world and we will further refine the algorithm. This will be the focus on Year 2 of the project. An abstract describing our preliminary work was submitted and accepted for presentation at the annual meeting of the American Society of Biomechanics.

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1. Introduction

Falling is a common problem for lower limb amputees, which can lead to reduced physical and emotional health. The overall aims of this project are to: 1) establish a baseline fall detection algorithm derived from simulated falls in a laboratory setting, and 2) utilize and refine the initial laboratory-based algorithm to provide detection of fall events during activities of daily living in real-world environments. The proposed research has two aims: 1) establish a baseline fall detection algorithm derived from simulated falls in a laboratory setting, and 2) utilize and refine the initial laboratory-based algorithm to provide detection of fall events during activities of daily living in pragmatic, real-world environments. To achieve these aims we will perform two human subject experiments. The first experiment will use 30 non-amputee and 5 lower limb amputee individuals to simulate falls in a laboratory setting while wearing the sensor. The sensor will record the motion of the body while falling so that we can create an algorithm to detect a fall in comparison to normal daily activities. The second experiment will recruit 40 lower limb amputees to wear the sensor in the real-world. Amputees will use the sensor for an 8-week period. During that time the sensor will record their motion and detect when a fall occurs. Participants will also report weekly about any fall events that were not detected so that the algorithm can be improved. The outcomes from this two-year project will be new information for clinicians to better understand the number of falls that occur for lower limb amputees. This work represents an initial pilot study to collect data for the fall detection algorithm and lead to future studies where large numbers of amputees will be supplied with the sensors in order to better quantify falling in the larger amputee community and other communities that are at high risk for falling.

2. Keywords

Biomechanics, amputation, balance, fall detection, sensors, algorithms

3. Accomplishments

What were the major goals of the project?

Specific Aim 1: Establish a baseline fall detection algorithm derived from simulated falls in a laboratory setting.	**Timeline (months)**	**Status**
Major Task 1.1: Human subject experiment (n=35)	1-7	
Milestone 1.1.1: Obtain approval from the governing Institutional Review Boards.	2	Complete
Milestone 1.1.2: Complete enrollment of all participants and collect experimental data.	5	Complete
Major Task 1.2: Analyze Human Subject Data	5-8	
Milestone 1.2.1: Perform machine learning analysis of falling data from healthy subjects to determine the initial fall detection algorithm.	1	Complete
Milestone 1.2.2: Perform hypothesis tests to evaluate the effectiveness of the falling algorithm.	1	Complete
Milestone 1.2.3: Implement the algorithm in the IMU sensor.	0.5	Currently in Progress)
Milestone 1.2.4: Complete writing of manuscript and conference abstract describing initial algorithm development and results.	2	Two Abstracts Completed, Manuscript in Progress

Specific Aim 2: Utilize and refine the initial laboratory-based algorithm to provide detection of fall events during activities of daily living in pragmatic, real-world environments.	**Timeline (months)**	
Major Task 2.1: Human subject experiment (n=40)	6-21	
Milestone 2.1.1: Obtain approval from the governing Institutional Review Boards.	2	Complete
Milestone 2.1.2: Complete enrollment of all participants and collect experimental data.	15	Currently in Progress)
Major Task 2.2: Analyze Human Subject Data	21-24	
Milestone 2.2.1: Perform machine learning analysis on complete dataset to determine final algorithm with all data.	2	TBD
Milestone 2.2.2: Perform hypothesis tests to evaluate the effectiveness of the falling algorithm in the real-world.	3	TBD
Milestone 2.2.3: Complete writing of manuscript and conference abstracts describing the algorithm development, validation and results.	3	TBD

What was accomplished under these goals?

In Year 1, our goal was to establish a baseline fall detection algorithm derived from simulated falls in a laboratory setting. Using data from our first 15 non-amputee subjects, we developed an initial algorithm to detect different fall types with an inertial measurement unit (IMU) placed on the individual's shank in preparation for application and validation on individuals with a lower limb amputation. Tri-axis accelerometer and gyroscope data were recorded from these devices at 100-Hz while subjects completed an overground course with simulated falls and near-falls. The course was designed to simulate activities of daily living (ADL: walking/running in a straight line at a self-selected pace, navigating turns, sitting and rising from a chair, laying down and getting up from a bed, picking up an object on the floor, and ascending/descending stairs/slopes). Subjects performed 4 types of simulated falls: forward/backward trips (i.e., subjects walked forward/backward until they impacted a fall pad and fell) and left/right lateral falls (i.e., subjects stood with their left/right side adjacent to the fall pad while a lab technician pushed them until they lost balance and fell onto the fall pad). For the simulated near falls, subjects walked until their left/right foot struck the fall pad and then recovered from the stumble.

Raw data were analyzed using the MATLAB Classification Learner Toolbox. First, data were split into two categories: ADL or Fall. Data were divided into 0.5 second windows with a 0.25 second overlap. During these 0.5 second windows, a total of 40 features were computed. Data were randomly split into training (80%) and model verification (20%) sets for each subject and each category. Three different classification algorithms were used for activity classification and validated with 5-fold cross validation: support vector machine with a cubic kernel (SVM), K nearest neighbor with weighted dimensions (kNN), and a bagged decision tree ensemble (Tree).To determine algorithm accuracy, a simple control scheme was created. First, models were implemented on the verification data set. A fall was identified if at least two adjacent windows contained a label associated with a fall. If this occurred within the duration of the fall (~1s), a correct fall classification was made. Falls were labelled by type: forward/backward trips and lateral falls with the sensor placed on the inside/outside leg. Finally, fall detection accuracy was calculated, defined as the number of correct classifications divided by total number of falls.

The results showed forward falls had the lowest detection accuracy for each algorithm. When falling forward, participants can more easily protect their body with their hands and knees, acting to reduce the acceleration on impact. On average, inside falls had the highest detection accuracy. The inside shank is often the first part of the body that impacts the ground during lateral falls, possibly contributing to the higher accuracy. This is in contrast to previous work that noted highest classification accuracy with backward falls when an IMU sensor is placed on the waist of each participant. This initial study highlighted that fall detection accuracy is not the same across fall types and classification algorithms. An abstract describing this work was accepted and presented at the annual meeting of the *American Society of Biomechanics* (attached in Appendix). We are currently working on a peer-reviewed journal article describing this work.

In Year 2, we completed the data collection for Aim 1 (30 healthy and 5 individuals with a lower limb amputation) and sought to further develop the algorithm to detect falls in real-time. Using the collected experimental data described above, we input the data into a customized machine learning pipeline to further process the data and optimize the settings for the classification algorithm. Data was divided into Training Data (algorithm construction, 30 intact participants), Validation Data (feedback for optimization, 2 amputee participants), and Test Data (validation of classifier ability, 3 amputee participants). Falling data was outnumbered compared to the ADL data, so we used a Synthetic Minority Oversampling Technique (SMOTE) to create a balanced dataset. The trained classifier was specifically developed for deployment on a platform with limited processing power and memory (ESP32 processor with 512 KB of onboard memory) which guided the selection of two possible classifiers. The first classifier tested was a Multilayer Perceptron neural network (MLP). An MLP is not time dependent, classifications utilize raw data directly (6 raw IMU channels) without a sliding time window, and can be modified for low computing power by reducing the number of layers and neurons [4]. The second classifier utilized a Support Vector Machine (SVM) with a Radial Basis Function kernel which showed promising results in distinguishing near-falls from ADL [5]. To reduce the classifier power requirement and size, input features were restricted to resultant acceleration and angular velocity ($x^2+y^2+z^2= r$ for each). The SVM utilized a sliding time window, the length and overlap of which was optimized by the pipeline to obtain the highest detection accuracy. The number of support vectors is influenced by the number of samples in the training data (a larger dataset requires more memory), so after using SMOTE to balance the dataset the pipeline randomly under sampled the Training Data to reduce the size of the classifier. Classifiers were then compared by their ability to accurately detect both falling events and ADL events in the Test Data.

The results showed on average, the MLP had better detection ability and a smaller memory requirement. An important note, the MLP was trained using all Training Data while the SVM was trained with a reduced portion of the Training Data which will likely adversely affect real-world performance. Furthermore, the MLP utilized all 6 channels independently whereas the SVM was reduced to two resultant features. This suggests that training with the full, unmodified feature set can further increase classifier performance. A conference abstract was submitted and accepted to be presented at the *North American Congress on Biomechanics* on in August, 2022 in Ottawa, Canada.

What opportunities for training and professional development has the project provided?

This project has provided professional development opportunities for graduate students Lindsey Lewallen and Mojtaba Mohasel through technical writing and presenting their work at scientific conferences.

How were the results disseminated to communities of interest?

The results of our Year 1 activities were accepted and presented at the annual meeting of the *American Society of Biomechanics* in August, 2021. A research poster describing this work was also presented at the UT Austin Department of Mechanical Engineering Graduate Student Research Poster Session. A manuscript describing this work is currently in preparation for submission to a peer reviewed journal. The results of our Year 2 activities were accepted and will be presented at the *North American Congress on Biomechanics* in August, 2022. The conference abstracts and the research poster are attached in the Appendix.

What do you plan to do during the next reporting period to accomplish the goals?

We are currently in the first year of a no-cost extension as the project has been significantly delayed due to COVID restrictions. We are currently incorporating the classifiers into the IMU firmware and performing benchtop testing. Once the algorithms are validated, we will perform the data collection in real-world environments and perform the analyses outlined in Aims 2.1 and 2.2. We will then complete the writing of a manuscript and additional conference abstract describing the algorithm development, validation and fall detection results.

4. Impact

What was the impact on the development of the principal discipline(s) of the project?

Nothing to Report at this time as the project is still ongoing.

What was the impact on other disciplines?

Nothing to Report.

What was the impact on technology transfer?

Nothing to Report.

What was the impact on society beyond science and technology?

Nothing to Report.

5. Changes/Problems

Nothing to Report.

6. Products

Publications, conference papers, and presentations

Lewallen, L.K., Pew, C.A., Wurdeman, S.R., and Neptune, R.R. (2021). Detection of different fall types in healthy young adults. *45th Annual Meeting of the American Society of Biomechanics*, August 10-13, Atlanta, GA.

Mohasel, M., Lewellen, L.K., Pew, C., Neptune, R.R. (2022). A machine learning scheme to identify falling for lower limb amputees. *North American Congress on Biomechanics*, August 21-25, Ottawa, ON, Canada.

Lewallen, L.K., Pew, C.A., Wurdeman, S.R., and Neptune, R.R. (2022). Detection of different fall types in healthy young adults. *Department of Mechanical Engineering Graduate Student Research Poster Session*, March 4, Austin, TX.

Website(s) or other Internet site(s)

Nothing to Report.

Technologies or techniques

Nothing to Report.

Inventions, patent applications, and/or licenses

Nothing to Report.

Other Products

Nothing to Report.

7. Participants & Other Collaborating Organizations

What individuals have worked on the project?

Name:	Richard R. Neptune
Project Role:	PI
Researcher Identifier:	NIH eRA Commons ID: rneptune
Nearest person month worked:	1
Contribution to Project:	Dr. Neptune helped put together the IRB application for approval from both UT Austin and HRPO. He also supervised the graduate student work on the project.
Name:	Lindsey Lewallen
Project Role:	Graduate Student
Researcher Identifier:	N/A
Nearest person month worked:	6
Contribution to Project:	Ms. Lewallen helped put together the two IRB applications and has been working with the machine learning algorithms to be used in the project.
Name:	Corey Pew
Project Role:	Collaborator
Researcher Identifier:	N/A
Nearest person month worked:	1
Contribution to Project:	Dr. Pew has helped to refine the machine learning algorithms to work in real-time.

Has there been a change in the active other support of the PD/PI(s) or senior/key personnel since the last reporting period?

Nothing to Report.

What other organizations were involved as partners?

- **Organization Name:** Hanger Clinic
- **Location of Organization:** Austin, TX
  - **Partner's contribution to the projec**t: Collaboration, help with subject recruitment.

- **Organization Name:** Montana State University,
- **Location of Organization:** Bozeman, MT
  - **Partner's contribution to the projec**t: Collaboration, help with algorithm development.

8. Special Reporting Requirements

Collaborative Awards: Not applicable

Quad Charts: Attached in Appendix.

9. Appendices

DETECTION OF DIFFERENT FALL TYPES IN HEALTHY YOUNG ADULTS

Lindsey K. Lewallen[1], Corey A. Pew[2], Shane R. Wurdeman[3], and Richard R. Neptune[1]
[1]Walker Department of Mechanical Engineering, The University of Texas at Austin, Austin, TX
[2]Department of Mechanical and Industrial Engineering, Montana State University, Bozeman, MT
[3]Department of Clinical and Scientific Affairs, Hanger Clinic, Austin, TX
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Introduction

Individuals with a lower-limb amputation are at an increased risk of falling compared to young healthy adults. Approximately 50% of individuals with unilateral amputation report at least one fall annually.[1,2] Falls are dangerous, occasionally leading to injury, hospitalization or death.[3] Fortunately, individuals who obtain aid within 1 hour of a fall have a 50% increased survival rate compared to individuals who obtain aid after 72 hours.[4] Thus, devices that have the ability to detect falls and alert proper personnel could serve to help lower the consequences of falling for individuals with a lower-limb amputation.

A number of studies have developed body worn sensors that can detect fall events. These devices primarily use inertial measurement units (IMUs) to record signals from 3-axis accelerometers, gyroscopes, and/or magnetometers. Individuals with a lower-limb amputation utilize a prosthesis that allows for fall detection sensors to be conveniently integrated within the prosthesis (e.g., directly attached to the pylon). However, it is not clear if such sensors are able to detect a wide range of fall types. Therefore, the purpose of this study was to investigate the accuracy of detecting different fall types with an IMU placed on an individual's shank in preparation for application and validation on individuals with a lower limb amputation.

Methods

IMU sensors (XSens, Enschede, Netherlands) were placed on both shanks of 15 healthy young adults in positions analogous to the pylon of a prosthesis distal to the knee. Tri-axis accelerometer and gyroscope data were recorded from these devices at 100-Hz while subjects completed an overground course with simulated falls and near-falls. The course was designed to simulate activities of daily living (ADL: walking/running in a straight line at a self-selected pace, navigating turns, sitting and rising from a chair, laying down and getting up from a bed, picking up an object on the floor, and ascending/descending stairs/slopes). Subjects performed 4 types of simulated falls: forward/backward trips (i.e., subjects walked forward/backward until they impacted a fall pad and fell) and left/right lateral falls (i.e., subjects stood with their left/right side adjacent to the fall pad while a lab technician pushed them until they lost balance and fell onto the fall pad). For the simulated near falls, subjects walked until their left/right foot struck the fall pad and then recovered from the stumble.

Raw data were analysed using the MATLAB Classification Learner Toolbox. First, data were split into two categories: ADL or Fall. Data were divided into 0.5 second windows with a 0.25 second overlap. During these 0.5 second windows, a total of 40 features were computed (Table 1). Data were randomly split into training (80%) and model verification (20%) sets for each subject and each category. Three different classification algorithms were used for activity classification and validated with 5-fold cross validation: support vector machine with a cubic kernel (SVM), K nearest neighbor with weighted dimensions (kNN), and a bagged decision tree ensemble (Tree).[5]

Table 1: Features extracted for each 0.5 s window for each accelerometer (accel) and gyroscope (gyro).

Vector resultant (r_{accel}, r_{gyro})	Median, Mean, Standard Deviation, Skewness, Kurtosis, IQR, Minimum, Maximum
Each axis (x_{accel}, y_{accel}, z_{accel}, x_{gyro}, y_{gyro}, z_{gyro})	Mean, Max, Min, IQR

To determine algorithm accuracy, a simple control scheme was created. First, models were implemented on the verification data set. A fall was identified if at least two adjacent windows contained a label associated with a fall. If this occurred within the duration of the fall (~1s), a correct fall classification was made. Falls were labelled by type: forward/backward trips and lateral falls with the sensor placed on the inside/outside leg. Finally, fall detection accuracy was calculated, defined as the number of correct classifications divided by total number of falls (Table 2).

Results and Discussion

Forward falls had the lowest detection accuracy for each algorithm. When falling forward, participants can more easily protect their body with their hands and knees, acting to reduce the acceleration on impact. On average, inside falls had the highest detection accuracy. The inside shank is often the first part of the body that impacts the ground during lateral falls, possibly contributing to the higher accuracy. This is in contrast to previous work that noted highest classification accuracy with backward falls when an IMU sensor is placed on the waist of each participant.[6]

Significance

This study highlighted that fall detection accuracy is not the same across fall types and classification algorithms. Future work should seek to improve detection of forward falls (e.g., placing sensors in different locations, implementing different classification algorithms such as threshold algorithms,[7] and exploring different features) and validate these results on individuals with a lower limb amputation.

Acknowledgments

This work was supported by CDMRP W81XWH2010164.

References

[1]Miller WC, et al. *Arch Phys Med Rehabil.* 2001. [2]Kulkarni J, et al. *Physiotherapy.* 1996. [3]Rubenstein LZ, et al. *Age Ageing*. 2006. [4]Gurley RJ, et al. *N Engl J Med.* 1996. [5]Pew C, et al. *IEEE.* 2018. [6]Hwang SY, et al. *Int Conf on CS and Tech.* 2012.

Table 2: Accuracy for each type of fall and algorithm

	Type of Fall				
	Forward	**Backward**	**Outside**	**Inside**	**All Falls**
SVM	76.7%	93.3%	100%	100.0%	92.5%
kNN	73.3%	90.0%	90.0%	100.0%	88.3%
Tree	76.7%	86.7%	93.3%	93.3%	87.5%

A Machine Learning Scheme to Identify Falling for Lower Limb Amputees

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[2]Walker Department of Mechanical Engineering, The University of Texas at Austin, Austin, TX
[3]Clinical and Scientific Affairs, Hanger Clinic, Austin, TX
Email:*Corey.Pew@montana.edu

Introduction

Falls present a major health risk for individuals with lower limb amputation [1]; however, real-world falls are difficult to objectively measure. One method to detect falls is to use inertial measurement units (IMUs) and machine learning to classify falling events relative to normal activities of daily living [2]. However, most existing algorithms process the data offline and there is a delay in identifying a fall. The purpose of this study was to develop machine learning methods that can detect fall incidence in the amputee population in real-time.

Methods

Fall detection algorithms were developed using data from 30 intact and 5 lower limb amputee participants. An IMU sensor attached in the middle of the shank measured acceleration and angular velocity in the x, y, and z directions. Participants navigated a course in the laboratory that consisted of various activities of daily living (ADL) and controlled falling. The collected data was used as input to a customized machine learning pipeline to process the data and optimize settings for a classification algorithm [2]. Data was divided into Training Data (algorithm construction, 30 intact participants), Validation Data (feedback for optimization, 2 amputee participants), and Test Data (validation of classifier ability, 3 amputee participants). Falling data was outnumbered compared to ADL and so the pipeline utilized the Synthetic Minority Oversampling Technique (SMOTE) [3] to create a balanced dataset. The trained classifier is specifically developed for deployment on a platform with limited processing power and memory (ESP32 processor with 512 KB of onboard memory) which guided the selection of two possible classifiers. The first method tested was a Multilayer Perceptron neural network (MLP). An MLP is not time dependent, classifications utilize raw data directly (6 raw IMU channels) without a sliding time window, and can be modified for low computing power by reducing the number of layers and neurons [4]. The second method utilized a Support Vector Machine (SVM) with a Radial Basis Function kernel which showed promising results in distinguishing near-falls from ADL [5]. To reduce the classifier power requirement and size, input features were restricted to resultant acceleration and angular velocity ($x^2+y^2+z^2= r$ for each). The SVM utilized a sliding time window, the length and overlap of which was optimized by the pipeline to obtain the highest detection accuracy. The number of support vectors is influenced by the number of samples in the training data (a larger dataset requires more memory), so after using SMOTE to balance the dataset the pipeline randomly under sampled the Training Data to reduce the size of the classifier. Classifiers were then compared by their ability to accurately detect both falling events and ADL events in the Test Data.

Results and Discussion

On average, the MLP had better detection ability and a smaller memory requirement (Table 1).

Table1: Comparison of detection rates between MLP and SVM algorithms. Training Data was used to create the algorithm, Validation Data (Val Data) was used for optimization, and Test Data were used to assess the performance of the final classifiers. Values for Fall indicate the rate for identifying falls while ADL indicates the rate for identifying activities of daily living. Run Time Size indicates the size of the compiled C-Code classifier.

Data Type	MLP		SVM	
	Fall	ADL	Fall	ADL
Training	99%	94%	99%	93%
Val Data	88%	95%	84%	84%
Test Data	87%	93%	83%	82%
Run Time Size	77 KB		344 KB	

An important note, the MLP was trained using all Training Data while the SVM was trained with a reduced portion of the Training Data which will likely adversely affect real-world performance. Furthermore, the MLP utilized all 6 channels independently whereas the SVM was reduced to two resultant features. This suggests that training with the full, unmodified feature set can increase classifier performance. In future work, we will incorporate these classifiers into hardware that will be used with lower limb amputees to determine the validity of the laboratory-based classifier and objectively quantify falling in the real world. Final algorithm selection will be determined by memory usage, processor performance, and prediction speed during real-time use on our ESP32 hardware.

Significance

In this study, we developed two algorithms capable of detecting falls in real time on limited processor and memory hardware. Previous research with a similar single sensor placement has obtained 85% detection for fall and ADL [6], however, they were not limited by processor or memory. These fall detection algorithms, when implemented on individuals in the real world, will have the ability to provide clinicians with accurate and objective information about patient falling. This will allow for a better understanding of which patients may need interventions to mitigate future falling such as modifications to their prosthetic components or prescription of specific exercise protocols.

Acknowledgements

Funding provided by CDMRP Grant W81XWH-20-1-0164. The authors thank Bryce Billings from Hanger Clinic for feedback on this work.

References

1) Miller et al., Arch. Phys. Med. Rehab. (82)2001l; **2)** Mohasel & Pew, 45th Meeting ASB, 2021; **3)** Chawla et al., Journal of AI Research, (16)2002; **4)** Goodfellow et al, Deep Learning, 2015; **5)** Aziz et al, IEEE, 2012; **6)** Ramón et al, Sensors, (18)2018

Detection of Different Fall Types in Healthy Young Adults

Lindsey K. Lewallen[1], Corey A. Pew[2], Shane R. Wurdeman[3], and Richard R. Neptune[1]

[1] Walker Department of Mechanical Engineering, The University of Texas at Austin, Austin, TX
[2] Department of Mechanical and Industrial Engineering, Montana State University, Bozeman, MT
[3] Department of Clinical and Scientific Affairs, Hanger Clinic, Austin, TX

Introduction

- Individuals with a **lower-limb amputation** are at an increased **risk of falling** compared to healthy adults.[1,2]
- **Body worn sensors** have the potential to **detect fall events** and alert proper personnel.
- Body worn sensors primarily use **inertial measurement units** (IMUs) to record signals from 3-axis accelerometers, gyroscopes, and/or magnetometers.
- Individuals with a lower-limb amputation use a prosthesis that allow for fall detection sensors to be conveniently attached to the pylon (Fig. 1).
- However, it is not clear if such sensors can detect a wide range of **fall types**.

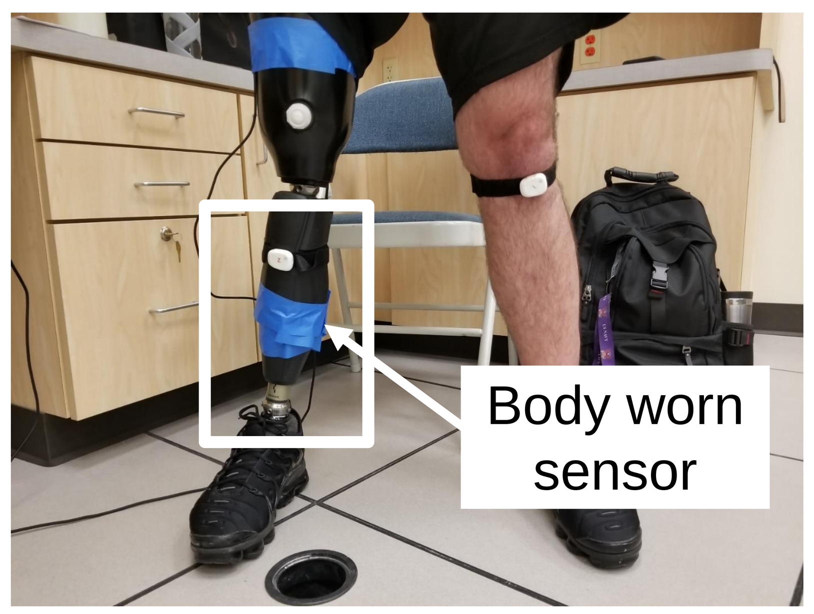

Figure 1: Location of body worn sensor on an individual with a lower-limb amputation.

Purpose

Investigate the **accuracy** of machine learning algorithms in detecting **different fall types** with an IMU placed on an individual's shank.

Methods

Experimental Data:

- Tri-axis **accelerometer** and **gyroscope** data were recorded from IMU sensors placed on both shanks of 15 healthy young adults.
- Subjects completed an overground course designed to simulate **activities of daily living** (ADL) and performed 3 types of **simulated falls/near falls**:
  - **Trips**: subjects walked forward (backward) until they impacted a fall pad and fell.
  - **Lateral falls**: subjects stood with their left (right) side adjacent to the fall pad and a lab technician pushed them onto the pad (Fig. 2).

Methods cont.

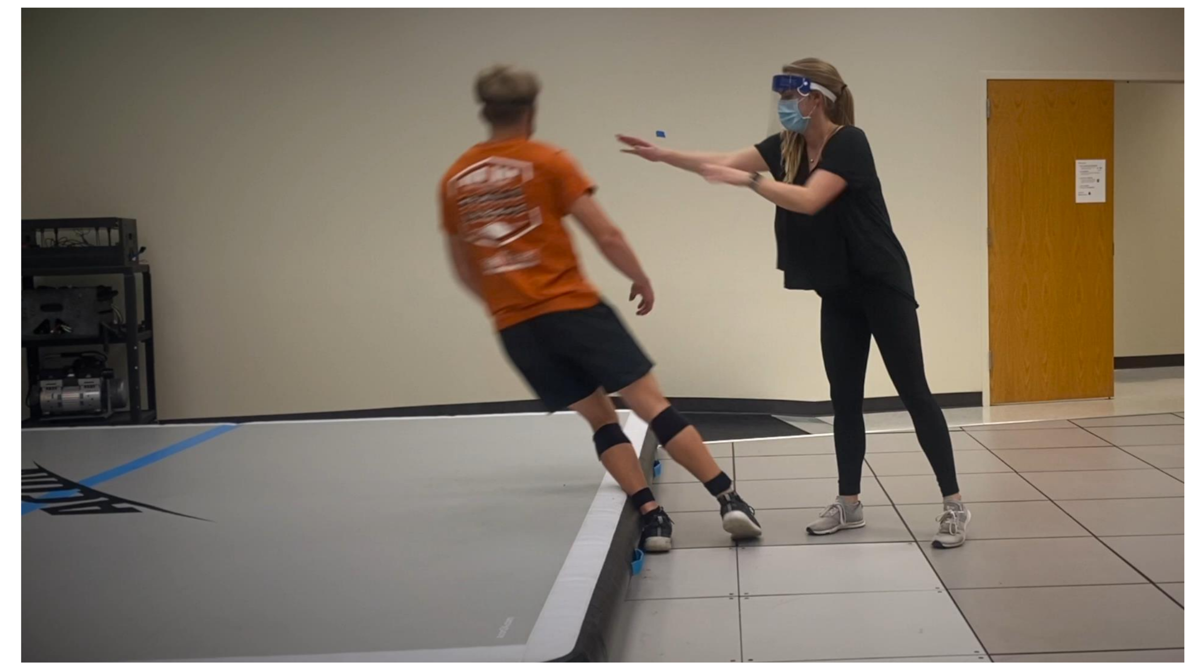

Figure 2: Lateral fall.

  - **Near falls**: subjects walked until their left (right) foot struck the fall pad and recovered from the stumble

Machine Learning Algorithms:

- Data were split into two categories (**ADL** or **Fall**) and divided into 0.5s windows with a 0.25s overlap.
- **40 features** were computed for each window (Table 1).

Table 1: Features extracted for each 0.5 s window for each accelerometer (accel) and gyroscope (gyro).

Vector resultant (r_{accel}, r_{gyro})	Median, Mean, Standard Deviation, Skewness, Kurtosis, IQR, Min, Max
Each axis (x_{accel}, y_{accel}, z_{accel}, x_{gyro}, y_{gyro}, z_{gyro})	Mean, Max, Min, IQR

- Data were randomly split into training (80%) and model verification (20%) sets for each subject and category.
- **Support vector machine** with a cubic kernel (SVM), **K nearest neighbor** with weighted dimensions (kNN), and **bagged decision tree** ensemble (Tree)[3] were used for classification and validated with 5-fold cross validation.

Accuracy Calculation:

- A fall was identified when 2+ adjacent windows contained a fall label and was correctly classified if this occurred within the duration of the fall (~1s).
- Falls were separated by type: **forward** and **backward trips** and **lateral falls** with the sensor placed on the **inside** or **outside** leg.
- Fall detection accuracy was defined as the number of correct classifications divided by total number of actual falls (Table 2).

Results

Table 2: Accuracy for each type of fall and algorithm.

	Type of Fall				
	Forward	**Backward**	**Outside**	**Inside**	**All Falls**
SVM	81.7%	93.3%	96.7%	96.7%	92.1%
kNN	73.3%	90.0%	93.3%	100.0%	87.2%
Tree	63.3%	85.0%	86.7%	96.7%	85.4%

- **Forward falls** had the **lowest detection accuracy** for each algorithm while **inside falls** had the **highest detection accuracy** (Table 2).

Discussion and Significance

- **Fall detection accuracy** is **not the same** across fall types and classification algorithms.
- When falling forward, participants can more easily protect their body with their hands and knees, acting to reduce the acceleration on impact.
- The inside shank is often the first part of the body that impacts the ground during lateral falls.
- Previous work noted highest classification accuracy with backward falls when an IMU sensor is placed on the waist of each participant.[4]
- Future work should seek to improve detection of forward falls (e.g., different classification algorithms such as threshold algorithms[4])
- Future work should validate these results on individuals with a lower limb amputation.

References & Acknowledgements

[1]Miller WC, et al. *Arch Phys Med Rehabil.* 2001.
[2]Kulkarni J, et al. *Physiotherapy.* 1996.
[3]Pew C, et al. *IEEE.* 2018.
[4]Hwang SY, et al. *Int Conf on CS and Tech.* 2012.

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Determination of fall risk for lower limb amputees

Log Number: OP190008
Award Number: W81XWH2010164

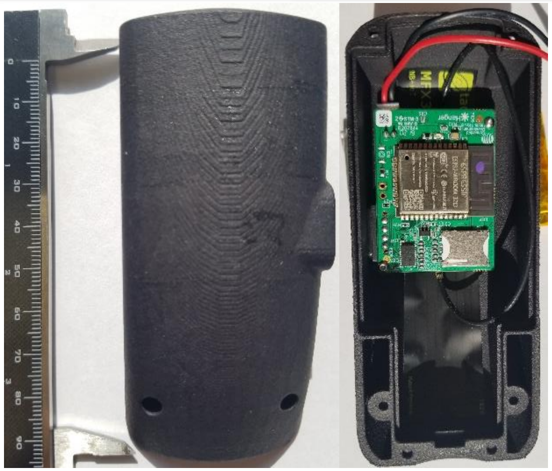
PIs: Richard R. Neptune, PhD, Shane R. Wurdeman, PhD, CP **Org:** The University of Texas at Austin **Award Amount:** $346,373 4/2020 to 3/2022

Study Aims

- Establish an initial fall detection algorithm derived from simulated falls in a laboratory setting (Aim 1).
- Utilize and refine the initial laboratory-based algorithm to provide detection of fall events during activities of daily living in pragmatic, real-world environments (Aim 2).

Approach

- Conduct a human subject experiment to create a baseline algorithm from control and amputee subjects performing simulated falls in the laboratory setting (n=30 control, n=5 amputee).
- Conduct a human subject experiment using lower limb amputees to refine the algorithm for use in real-world environments (n=40 amputees).
  - Amputees will wear the sensor for 8-weeks during their normal daily living activities.
  - Fall events will be reported weekly to provide iterative updates to the detection algorithm.



AT&T LTE Activity Device motion sensor. This sensor contains 3-axis accelerometer, gyroscope and magnetometer to measure human motion and can upload data to the AT&T cellular LTE network in real-time.

Timeline and Cost

Activities CY	1	2
Perform in lab testing (n=35) to produce an initial fall detection algorithm.	Aim 1	
Perform real-world experiment (n=40) to evaluate and update the initial fall detection algorithm.		Aim 2
Estimated Budget ($K)	**$186**	**$160**

Updated: July 30, 2020

Goals/Milestones

CY1 Goals – Project initiation

- ❑ Complete IRB approval
- ❑ Complete Aim 1 experimental protocol
- ❑ Begin analysis of data (Aim 1)
- ❑ Begin recruiting for Aim 2 protocol
- ❑ Disseminate initial results

CY2 Goals – Testing, analysis and recruitment

- ❑ Complete human subject recruitment and testing (Aim 2)
- ❑ Complete analyses of data (Aims 1 and 2)
- ❑ Complete results dissemination

Budget Information:

Projected Expenditures: $346,373
Actual Expenditure: N/A