26th Annual IEEE High Performance Extreme Computing Virtual Conference, 19-23 September 2022

Walker Activity Tracking Using Machine Learning

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***Abstract*—An accurate, economical, and reliable algorithm for detecting falls in persons ambulating with the assistance of an orthopedic walker is crucially important for elderly and patients recovering from surgery. Existing tracking device that must be wore on the body at all time. This project proposes a novel solution that employs motion tracking by attaching a wireless inertial measurement unit (IMU) sensor directly to the walker. IMU data are collected through the wireless link. Data augmentation and machine learning are applied to train a convolutional neural network (CNN) to classify the movements as standing, walking, or falling. Preliminary testing shows that the CNN can produce a classification accuracy of 99.8% and can consistently detect falls. The machine learning algorithm can potentially be targeted to the on-board embedded processor.**

***Index Terms*—orthopedic walker, fall detection, inertial measurement unit, deep learning**

I. Introduction

Life-threatening falls in the older population [1], often within the rehabilitation process after major surgery to the hip or leg area, are an increasing area of concern for patients and medical experts alike. Thus, technological advancements in fall detection or prevention have attracted increasing attention. The usage of sensor-based tracking can be effective in detecting falling motions of the walker through the employment of machine learning algorithms.

By monitoring the acceleration and relative coordinate position on all three axes of a person or object, it can be observed that drastic fall-like motions that cause the subject to lose balance or collapse to the ground usually result in significant spikes in acceleration on all three axes and noticeable deviations in gyroscopic position [2]. The challenge is to separate common motions such as walking or normal body gestures from falls while eliminate false positives.

Current products often abandon the usage of tracking devices due to irregularities and false positives in favor of simple medical alert systems self-actuated by the subject, which do not consider the possibility that a fall may cause life-threatening injuries that may incapacitate the subject and cause them to be unable to activate such systems. Inhibitions to speech and capability of motion can render medical alert systems ineffective, especially those that rely on direct communication between emergency services and the subject.

This paper has two main contributions: (1) It proposes a novel method of motion tracking and fall detection by attaching an IMU sensor directly on a walker; (2) It trains a deep learning model resulting in highly accurate and low false-positive detection and classification.

Figure 1. The IMU sensor [3] is attached to a walker [4] in this study

II. Methods of Study

We propose a device called smart walker that collects data from a battery-powered inertial measurement unit (IMU) sensor rigidly attached to the walker, which includes a tri-axial accelerometer and a tri-axial gyroscope. Directly measuring from the walker makes it less prone to false classification of excessive bodily motions. It also has the advantages of low cost, automatic on/off, and remote monitoring through a wireless data link. Subsequently, data obtained during testing are used to train a machine learning model consisting of a convolutional neural network (CNN) to classify the movements as either falling, walking, or standing. Data can be transferred via WiFi link for a real-time display or stored in the sensor itself for offline processing later.

A. Experimental Setup

The experimental apparatus consists of an IMU sensor secured to an orthopedic walker. The portable walker used in this case is the Drive Medical Trigger Release Folding Walker [4]. The IMU sensor is NGIMU [3], which provides a built-in tri-axial gyroscope with a range of 2,000 degrees per second and tri-axial accelerometer with a range of 16g. Both channels feature 16-bit analog to digital converter resolution. The IMU is secured to the center of the walker front bar as in Fig. 1, orientated with the horizontal x-axis, the vertical y-axis, and the z-axis for forward movement of the walker.

B. Data Collection

The NGIMU acquires time-series data for the 6 parameters (tri-axial acceleration and tri-axial rotation) at a rate of 50 Hz. Each data collection trial lasts 12 seconds. The IMU device communicates directly with a computer through Wi-Fi or Bluetooth. The data are saved in the computer in the

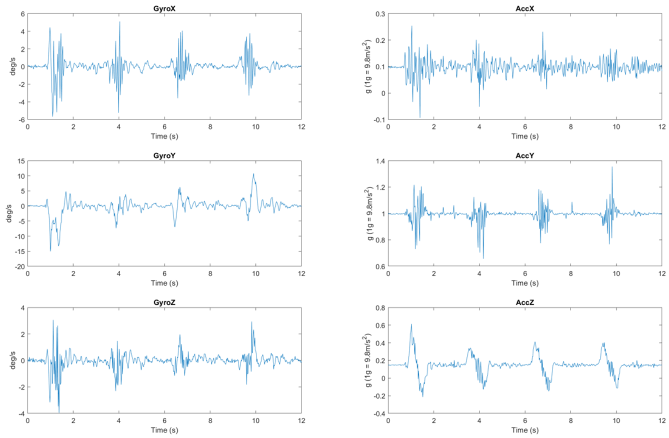

Figure 2. A sample data recorded with 4 walking steps in 12 seconds

format of a CSV file. The CSV file is then read and processed using MATLAB software.

For walking trials, 2 sets of data were collected. The subject was instructed to push the walker forward for 3 steps in the first set and 4 steps in the second set of trials. In this experiment, a step consists of the movements of one foot followed by another foot, which may be counted as two steps in common terms. This experiment treats two foot motions as one step since the they appear as a single burst of motion from the sensor data perspective as shown in Fig. 2. Similarly, trials of a simulated fall of the walker were conducted, where a subject holding a walker would lose their grip of the walker and lean forward, causing the walker to abruptly tip over or spin rapidly. After the sudden movement, the walker would remain stationary until the end of the trial. Only one fall event occurred in each trial. Lastly, data were collected for standing trials during which the subject simply held the walker with some upper body movement. Each active window is 2 seconds, and they are manually labeled as walking or falling.

C. Data Augmentation for Machine Learning

Training a machine learning model usually requires a large amount of data samples. The amount of data described above only consists of 30 falls and 210 walking steps. Data augmentation becomes necessary. In the case of walking, each labeled sample is 2 seconds in duration, which corresponds to 100 samples at 50 Hz. In order to generate more walking windows, the 2-second window was shifted by 5 samples and also by 10 samples in both directions, producing 4 augmented samples. Each augmented sample possesses at least 90% overlap with the originally labeled window. Data augmentation increases the active samples of walking by 5 times.

In the case of the fall data, in which there was only one fall per trial, the 2-second window containing the fall was shifted to the left by 14 samples and shifted to the right by 15 samples, effectively generating 30 samples per event of fall. This produced 900 samples of falling data. Similarly, data from standing trials was randomly sampled 36 times to produce 1,080 samples. Table I below lists the total data augmentation for each category of data collected.

Table I
CREATING TRAINING SAMPLES THROUGH DATA AUGMENTATION

Categories	Trials	Original Samples	Augmented Samples
Walking (3 steps)	30	90	450
Walking (4 steps)	30	120	600
Falling (1 fall)	30	30	900
Standing	30	-	1080

III. CONVOLUTIONAL NEURAL NETWORK

A six-layered convolutional neural network was trained to classify the data. The input of the CNN network is 100 points of 6-axis data collected by the IMU sensor, so the input feature size is 6-by-100. Data are first fed through four convolution layers used for feature extraction. Each layer encompasses 2-D filters for convolution, data pooling, and reLU functions. Data then enter two fully connected layers, which ultimately produce a single classification result. Finally, a softmax layer is used to output the 3-class classification results.

As described in Section II, data from 60 trials of walking, 30 trials of falling, and 30 rest trials were collected and labeled. Data augmentation was performed to increase the data to 1050 walking, 900 falling, and 1080 rest windows. A CNN was trained in Matlab to perform the task of 3-class classification. 80% of samples were randomly selected for training and the remaining 20% of samples were used for validation. The model was trained for 10 epochs. Results show that the CNN reached an overall classification accuracy 99.8%. There was only 1 miss-classification, which was a fall classified as walking. All other 605 samples of validation data were classified correctly.

We evaluated the machine learning model using 5 minutes of recorded data. Each sliding window is 2 seconds with 20% overlap with previous one. The model was able to detect all fall events without any false positive. As a side product, it can also obtain the step counts of walking.

IV. CONCLUSION AND FUTURE WORK

This study presents a novel approach to using deep learning models for physiology applications in an accurate, efficient, and effective way. Using an IMU device as a sensor, data were collected for cases of both walking and falling and, after data augmentation, a CNN model was trained for multi-class classification. Results of evaluating the model with validation data show that this method resulted in very high accuracy. In future work, we plan to implement the machine learning algorithm directly on the built-in processor, so the device can work even when wireless links are not available.

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