Smartphone-based Gait Analysis: A Boon for Accessibility

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With only three gait analysis centers in Western Canada, gait analysis is currently not an accessible, feasible, or cost-effective method of disease diagnosis, and screening. An often-overlooked marker of health, gait has been validated as an early marker for Alzheimer's disease, multiple sclerosis, Parkinson's disease, sports-related injuries, and chronic pulmonary disease. With the rise of smartphone use in Canada and across the world amongst children and seniors alike, smartphones are at the forefront of health research tools.

The aim of this study was to develop and investigate an automated smartphone-based gait analysis system capable of detecting and monitoring gait parameters similar to the golden standard GaitRite system. Smartphone-based gait analysis offers numerous benefits: in terms of cost savings, portability, customizability, patient tolerance, and deployment scalability. Measures of stride length and time variability, gait asymmetry, and cadence were successfully gleaned using this gait analysis algorithm.

Introduction

With the advent of powerful and portable smartphones which house a self-contained inertial measurement unit, a processing core, and touchscreen, smartphones are at the forefront of health technology research. the Robert Wood Johnson Foundation predicts the number of mobile health application will increase by a rate of 25% per year and 1.7 billion smartphone users worldwide will download health apps in 2018(Hawkins et al. 2018). Given these statistics, smartphone-based health tools are much more accessible and feasible for the developing world and developed world alike.

Gait is essentially the manner in which someone walks. Gait analysis by extension is the quantification of how someone walks through objective measures such as: step length, step time, cadence. Gait analysis is currently conducted using a costly and inaccessible video-based recording of markers placed at end-points of all or a subset of body segments (Webster et al. 2005). With each gait analysis costing $2125 USD per visit (Tunca et al. 2017), gait labs are not feasible for the use of the general public. In addition, with only three gait labs in all of Western Canada (Tunca et al. 2017), the accessibility to such gait analysis lacks even further.

Gait has been validated to predict and diagnose early Parkinson's disease, early Alzheimer's disease, congenital heart failure, patellar tendonitis, and chronic obstructive pulmonary disease (Chastan et al. 2019, Tunca et al. 2017). However, gait is often overlooked as a diagnostic tool. Gait analysis has been shown to be applicable to every demographic from children to seniors. Given the subjective nature of neurodegenerative disease diagnosis, objective quantitative measures from gait analysis could potentially improve and reduce error margins diagnosis if made accessible and cost-effective (Molloy et al. 1991).

The present study sought to develop an accessible, feasible, and non-invasive smartphone-based gait analysis tool that is capable of recreating parameters found in the golden standard of the GaitRite system. This smartphone-based tool offers numerous benefits: in terms of cost savings, portability, customizability, patient tolerance, and deployment scalability.

Materials and Methods

Data Acquisition

Data was acquired through a tri-axial accelerometer running on a One Plus 5 smartphone. The sampling rate was set to 70 captures per second.

Gait Procedure

Gait was recorded and analyzed using a smartphone-based inertial measurement unit. The smartphone was placed in the back pocket of the individual. The triaxial accelerometer was utilized to measure gait parameters. Each participant walked on the same 10-meter walkway. The gait task, performed in a well-lit environment, consisted of walking back and forth over a distance of 10 meters, at a self-selected pace. Video footage of the walking was also taken as a verification measure during the analysis of the gait.

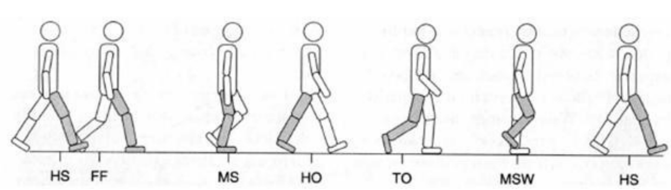

Figure 1: Depiction of gait cycle – Heel Strike (HS) signifies the beginning of a gait cycle and was used as a part of the gait extraction process

Noise elimination

When the smartphone samples the walking data, some noises will inevitably be collected. Noise is lower in amplitude and associated with a different frequency range than that of the true signal created by potential jostling of the smartphone during gait. Thus, the signal was passed through a Butterworth filter to attenuate the noise, but also leave the true signal unaffected.

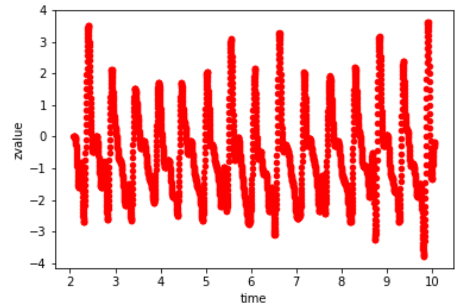

Figure 2: Z Axis Gait Signal After Filtering – Depiction of accelerometer data after being passed trhough a low pass filter

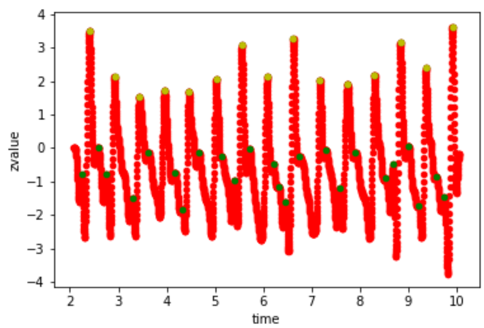

Figure 3: Z Axis with Gait Cycle Identification – Depiction of accelerometer signal after the algorithm identified the gait cycles

Analysis

When the smartphone is fixed in the back pocket of the individual, the gait cycle is clearly displayed on the Z-axis of the accelerometer. A gait cycle is defined as the time interval between two successive occurrences of the heel strike phase of walking. (Refer to figure 1 for depiction of gait cycle analyzed) Heel strike is characterized by the highest point of acceleration in a given gait cycle. An algorithm was designed to detect these peaks in acceleration. Thus, using the Z-dimension of acceleration, we extracted the peaks from S(n) or the filtered signal. A data point was defined if its value is greater than its previous and next one. Identifying the data points was found using the following argument:

$$P = \{ d_i \mid d_i > d_{i-1} \wedge d_i > d_{i+1} \}$$

Then a threshold was calculated to differentiate the peaks from the true peaks by using mu and sigma, or the mean and the standard deviation of all peaks respectively, and k is the user-defined constant of (1/3). The k value was determined by examining the error rate in relation to the observed values and choosing a value that minimized the error margins. The threshold was defined as:

$$T = \mu + k\Omega$$

$$TP = P > T$$

This calculation allowed for the automation of gait feature extraction as it created the data for stride time.

```python
import numpy as np
from scipy.signal import butter, lfilter, freqz
import matplotlib.pyplot as plt


def butter_lowpass(cutoff, fs, order=5):
    nyq = 0.5 * fs
    normal_cutoff = cutoff / nyq
    b, a = butter(order, normal_cutoff, btype='low', analog=False)
    return b, a

def butter_lowpass_filter(data, cutoff, fs, order=5):
    b, a = butter_lowpass(cutoff, fs, order=order)
    y = lfilter(b, a, data)
    return y

# Filter requirements.
order = 6
#fs = 30.0
# sample rate, Hz
fs = 30.0
#cutoff = 3.667  # desired cutoff frequency of the filter, Hz
cutoff = 0.7
# Get the filter coefficients so we can check its frequency response.
b, a = butter_lowpass(cutoff, fs, order)

y = butter_lowpass_filter(data['zvalue'], cutoff, fs, order)

data['zvalue'] = y
```

```python
data = pd.read_csv("C://Users//cassy//Downloads//KAI_TEST/ztests.csv")
print(data.head())
# data.plot.scatter('Time', 'Zvalue')
# false_peaks.plot.scatter('Time', 'Zvalue')
# true_peaks.plot.scatter('Time', 'Zvalue')

data.plot.scatter('time', 'zvalue', color='r')
plt.savefig('C://Users//cassy//Downloads//KAI_TEST/unfilteredfig.png')

print(data.columns.values)

false_peaks = pd.DataFrame(columns = ["time", "zvalue"])

for i in data.index:
    if i != 0 and i!= len(data.index)-1:
        z = data.at[i, "zvalue"]
        prev_z = data.at[i-1, "zvalue"]
        next_z = data.at[i+1, "zvalue"]
        if (z > prev_z) and (z > next_z):
            #temp = data.iloc[i:i+3, :]
            #print(type(temp))
            false_peaks = false_peaks.append(data.iloc[i, :], ignore_index=True)
            #print(data.iloc[i])
            #print(str(z) + "is peak")
```

```python
true_peaks = pd.DataFrame(columns = ["time", "zvalue"])
T = mu + (sigma*(1/3))
print(T)

for i in false_peaks.index:
    fp = false_peaks.at[i, "zvalue"]
    if (fp > T):
        true_peaks = true_peaks.append(false_peaks.iloc[i, :], ignore_index=True)

print(true_peaks.head())
```

Figure 4: Code used for gait identification and extraction

Stride length was measured from the up/downward movement of the center of mass from heel strike to heel strike. Movement in the vertical direction follows a circular trajectory during each single support phase; this is the inverted pendulum model. Using change in height (double integration of vertical acceleration) step length was able to be calculated (Zijlstra et al., 2003). The equation for the inverted pendulum model is as follows:

$$SL = 2\sqrt{2lh - h^2}$$

In terms of stride time, time was measured from the acceleration signal where heel strike is characterized as the highest point of acceleration in a given gait cycle. The acceleration data and time stamps were cross-referenced with video data as well as a sound cue. The coefficient of variation was used to calculate the variation in stride length and stride time.

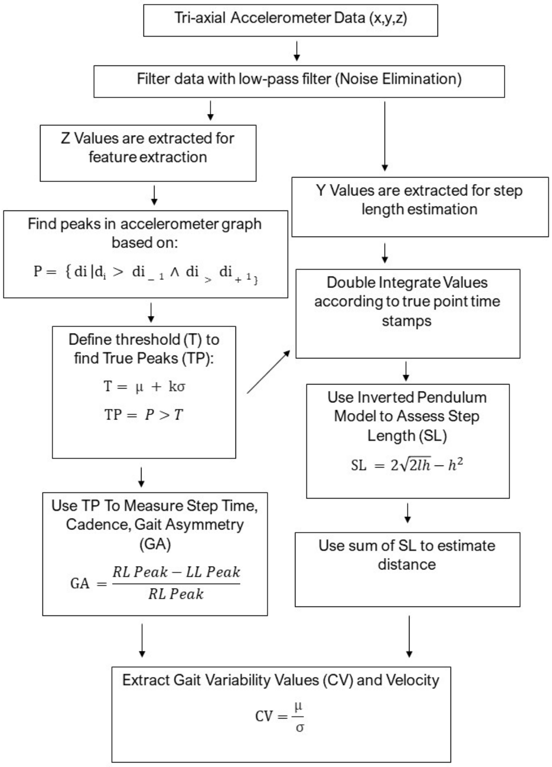

Figure 5: Representation of algorithm in flowchart form

We use the reported count as the golden standard to compare with the computed result. The golden standard means step length is calculated by the actual walking distance divided by the step count. The trial was repeated 35 times at different walking speeds and gait patterns.

Data Analysis

The stride length data, total distance data, and stride time data was cross-referenced with video footage and further referenced with the average step length calculated by standardizing the total distance walked. The walkway was marked out and the number of steps and interval between the steps of the subject took was noted by the investigator and compared to the data given by the smartphone-based system. These observations are defined as a the golden standard. Average error values were calculated in comparison with this data.

Results

In the present study, a total of 25 users were employed to examine the validity of a smartphone accelerometer in detecting user's motion and gait biometrics. The data from the 25 trials with the smartphone-based system were gathered and analyzed to get the gait parameters: step length, step time, total distance. These smartphone-based parameters were compared to the manual observations of step counting, and video camera recording the number of steps which served as the golden standard. Differences between the manual observations and the smartphone-based system were noted and the error between the golden standard and the smartphone were calculated. When the smartphone-based gait analysis results were compared to the video camera recording, and step counting, the error rates were nominal with an average error of 4.2% in step time, 2.3% in step length and 3.8% in distance.

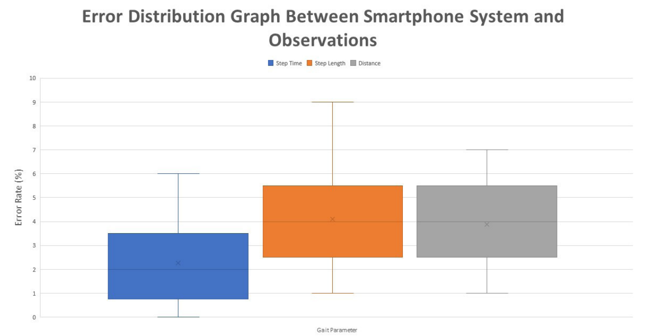

Figure 6: Error Rate of Gait Parameters when compared to the golden standard (manual step count)

Discussion

Treatment and rehabilitation of patients cannot occur until there is an accurate diagnosis. Though gait analysis is an effective and validated tool for disease diagnosis (Chastan et al. 2019, Tunca et al. 2017), it is not accessible to the general public. In this study, we have designed and developed a gait detection algorithm that utilized the acceleration signal from a built-in sensor to analyze gait parameters and potentially assess the abnormality of gait. This system poses several benefits that include, tracking gait progression over long periods of time, portable and user-friendly, and able to be used in any environment. The algorithm can extract gait parameters of individual users and can analyze the result in both normal and abnormal participants.

Since the accelerometer has been used to measure the abnormality of gait, there is a limitation in terms of device positioning. In addition, the size, shape, and weight of the smartphone may result in the movement artifact.

The next step of this research is to combine all the existing components into a fully-fledged free-living health monitoring system with smartphones. Given the portability and scalability of the smartphone, this study suggests that gait analysis can be used in virtually any environment.

The currently proposed method of gait analysis, however, has limitations. It is not able to differentiate between walking and other everyday activities such as car rides or going down stairs. Thus, further work is needed to develop an algorithm to distinguish walking from other everyday activities.

The currently proposed system has the potential to transform smartphones into health monitors designed to monitor health markers while the smartphone is carried during normal activities, namely, free-living walking. The present study's results suggest that gait analysis may soon be a feasible and accessible method of disease diagnosis in virtually any environment.

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