A Factorial Experiment to Investigate Naturalistic Factors Affecting Smartphone Gait Analysis

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Abstract—**Gait analysis involves analyzing data from body-mounted sensors in order to detect various ailments or aging. Prior work has utilized the accelerometers on Smartphones to collect gait data but required subjects to firmly attach the phones to their torsos, hip or other body parts. In real life, subjects prefer to place their phones in various pockets or bags, may wear loose or tight clothes which have been found to affect the quality of the accelerometer data gathered. In this paper, we report on factorial experiments to investigate what naturalistic factors affect accelerometer data gathered from unattached Smartphones. For a female subject, we found that the most impactful factor was wearing hard vs soft shoes. For a male subject, the most impactful factor was whether the phone was carried in an attaché case or not. Overall, we also found that none of the factors investigated produced an overwhelming response, which suggests that high-fidelity health assessments of various ailments could possibly be performed using gait data gathered in naturalistic settings (no need to attach smartphone precisely on subjects).**

Keywords—gait analysis, smartphone, naturalistic factors, factorial experiment.

I. Introduction

Major cerebral impairments, severe musculoskeletal disorders and aging can impact human gait especially while walking [10]. Walk tests are widely used as standard medical measures to assess major chronic ailments such as Chronic Obstructive Pulmonary Disease (COPD) and Congestive Heart Failure (CHF) [11]. For example, the 6-minute walk test requires the subject to walk for 6 mins back and forth over a measured distance. Gait analysis involves processing data from body-worn sensors in order to determine any gait characteristics and identify abnormalities [4]. Recently, gait analysis has utilized data gathered from the accelerometer of a user's smartphone while they were walking.

Much of the prior work typically required the subjects to firmly attach their smartphones to their bodies (e.g. on the lower back or torso). For instance, using this methodology, Cheng *et al* [11] estimated gait speed with a 94% accuracy using data gathered from accelerometers of smartphones attached to the subject's lower backs. However, in real life, subjects prefer to place their phones in various pockets or bags, or may wear loose or tight clothes that introduce noise into accelerometer data gathered [16]. These naturalistic factors make accurate gait analysis challenging.

In this paper, we report on brief experiments to investigate statistically significant naturalistic factors that influence the gait data gathered from a Smartphone's accelerometer. The factors we considered included the incline of the walking surface, placement of phone on the body, loose vs tight fitting clothing, shoe type and whether the phone was carried in an attache case (bag) (See figure 1). Due to the potentially large number of permutations of influencing factors and interactions, we utilized a factorial experimental design.

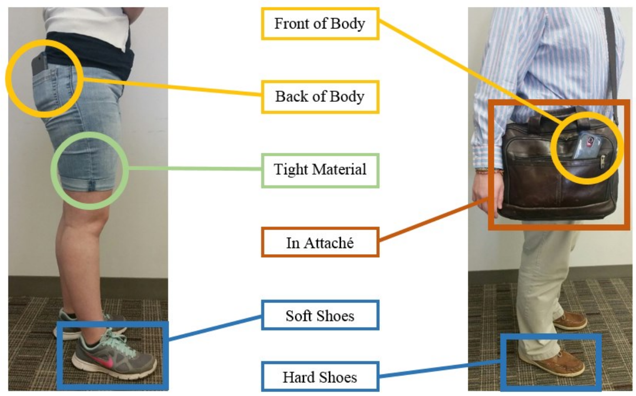

Figure 1 - Experimental Factors that could affect Gait inference

Factorial experimental design is a statistical method that is useful for estimating the effects of (and importance of) various factors on an experimental outcome. It is particularly useful for noisy data [9]. Compared to brute force exhaustive testing (one-factor investigations), factorial experiments also enable the investigation of interactions between experimental factors at reduced experimental costs.

Our Findings: We found that the most impactful experimental factor for our female subject was the hard versus soft soled shoes. The most impactful experimental factor for our male subject was whether the phone was in an attaché or not. We also found that none of the factors investigated produced an overwhelming response, which suggests that high-fidelity health assessments of various ailments could possibly be done using gait dat gathered from smartphones in naturalistic settings (no need to attach smartphone precisely on subjects).

II. Gait Data Collection

To gather gait data from a smartphone's accelerometer, we developed an app that leveraged Funf [13]. Funf is a third-party Android library that allows data from selected smartphone sensor(s) to be recorded at a chosen sampling rate and automatically transferred to a remote location for analysis.

III. GAIT DATA PRE-PROCESSING AND FEATURE EXTRACTION

Pre-processing raw accelerometer readings: First, to normalize the accelerometer readings for different phone orientations and positions in which the phone was carried (phone in different pockets or bags), the gravity-corrected magnitude of groups of *n* accelerometer readings was calculated using equation 1:

$$b(t) = \sqrt{{x_t}^2 + {y_t}^2 + {z_t}^2} - \frac{\sum_{i=1}^{n} \sqrt{{x_i}^2 + {y_i}^2 + {z_i}^2}}{n} \qquad (1)$$

Data smoothing to reduce effects of noise: Smartphone accelerometer data have lots of noise. To make the signal more stable, we calculated a moving average for a window size of 10 seconds (about 2000 accelerometer observations).

A. Gait Feature Extraction

A gait feature is a property that can be calculated from the phone's raw accelerometer data [5]. Human walking is a periodic motion. Hence, in addition to time domain features, some frequency domain features were also useful [2].

1) Time domain features: We explored time domain gait features that had been useful in prior work on gait. The number of steps taken per time window [2] can be calculated by finding the number of local maxima of the gravity-corrected magnitude of the accelerometer signals that exceed one standard deviation from the signal's mean [6]. Figure 4 shows example accelerometer data with the steps highlighted. Table 1 lists the time-domain features we explored.

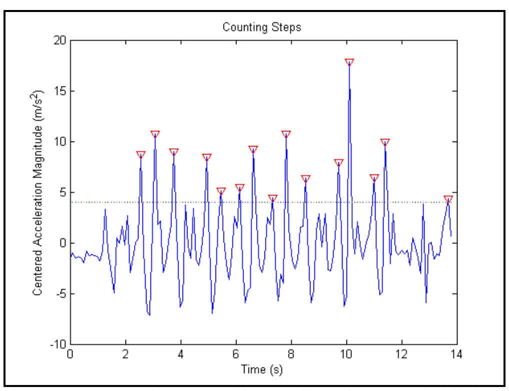

Figure 4 - Example Data with Number of Steps Highlighted

Frequency Domain Features: To convert the raw accelerometer data to the frequency domain, we applied the Discrete Fourier Transform (DFT). A one-sided Power Sectral Density (PSD) of a signal describes how the variance of data in the time domain is distributed over its frequency components. We calculated the one-sided PSD of the accelerometer data using Welch's overlapped segment averaging estimator algorithm, illustrated in Figure 6. From the PSD, we can gather where the energy of the signal is distributed in relation to its frequency. The highest peak in the figure is the fundamental frequency of the signal, which is about 1-5Hz for the activity of walking [2].

TABLE 1 – TIME DOMAIN GAIT FEATURES EXPLORED

Time Domain Feature	Definition
Number of Steps [2]	The number of steps taken in a given time interval
Average Step Length [3]	Average in the distance covered by each step
Average Step Time [3]	Average in the time covered by each step
Gait Velocity [2]	Ratio of the total distance covered by the total time
Cadence [2]	Ratio of the total number of steps by the total time
Skewness [2]	Asymmetry of the signal distribution
Kurtosis [2]	"Peakedness" of the distribution and the heaviness of its tail

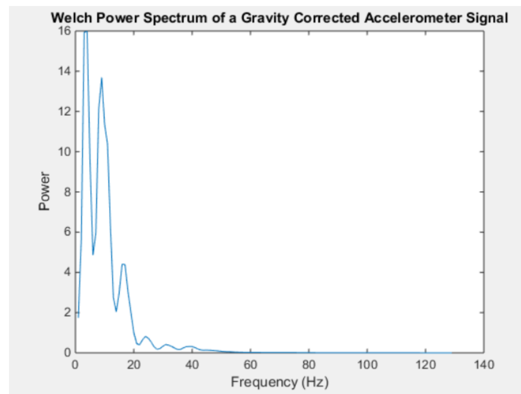

Figure 6 - PSD of Example Data Using Welch Algorithm

The frequency domain features of the signal that we extracted for gait classification were 1) the average power of the signal, 2) the ratio of high to low energy peaks of the PSD, 3) the signal to noise ratio of the signal, and 4) the total harmonic distortion of the signal. These features were selected these based on their effectiveness in prior research involving passive gait verification [2]. Table 2 summarizes the frequency domain features we extracted and their definitions.

TABLE 2 – FREQUENCY DOMAIN GAIT FEATURES EXPLORED

Frequency Domain Feature	Definition
Average Power [2]	The variance per unit time
Ratio of Spectral Peaks [2]	Ratio of the energies of low and high frequency bands
SNR	Power of whole signal / power of its computed noise
THD	Distortion of the whole signal compared to its harmonics

IV. FACTORIAL EXPERIMENT DESIGN

We performed a factorial experiment to investigate some everyday factors that influence gait attributes while a subject is carrying their phone naturally during normal human walking. Other activities, such as running, jogging, jumping and climbing stairs were not considered for the experiment. There were different covariates and experimental factors used for this experiment. Since covariates are subject-specific, they cannot be altered during the experiment and cannot be considered experimental factors. The experimental factors that we tested, which have been shown to impact gait are listed in Table 3 and illustrated in figure 1.

TABLE 3 – EXPERIMENTAL FACTORS INVESTIGATED

Factor and Representation	Levels	Description
Surface Incline **(A)**	Incline	approximately 5% grade
	Decline	approximately -5% grade
Body Placement of Phone **(B)**	Front of body	Front pocket
	Back of body	Back pocket
Material **(C)**	Loose	Gym shorts, sweatpants
	Tight	Jeans, dress pants
Shoe Type **(D)**	Hard	Dress shoes, high heels, hard tennis shoes
	Soft	Slippers, Dr. Scholls inserts, soft tennis shoes
In Attaché **(ABCD)**	Yes	Phone in purse or briefcase
	No	Phone not in purse or briefcase

Two participants (1 male weighing 280 pounds and 1 female weighing 155 pounds) were selected for this experiment. A brute force testing of the effects of all factors individually would have resulted in an extremely large number of trial runs (over 2^5). Therefore, we chose a factorial experimental design instead. Using a Resolution V one-half replication of a 2^5 design, we confounded the interaction of factors ABCD with E to reduce the trial runs by half and only considered $2^{(5-1)} = 2^4$ trial runs for the fractional factorial design. In order to gather enough data to determine the impact of measurement error on our results, we repeated these 16 runs 3 times each in a randomized order. We performed these 48 runs using an indoor ramp of approximately 5% incline to assess the varying factor's impact on gait. Table 4 below lists the trials performed in the factorial experiment. For each trial run, we collected time-series accelerometer data in the x, y, and z directions from the subject's smartphone. The data were streamed to a web server for further analysis using MATLAB. During each trial run, one of the experimental factors in Table 1 was varied and the subject walked in a straight line for 15 seconds while data was being gathered.

TABLE 4 – LIST OF TRIAL RUNS

	Surface Incline	Body Placement	Mate rial	Shoe Type	In Attaché
Trial 1	Decline	Back	Tight	Hard	Yes
Trial 2	Incline	Front	Tight	Hard	Yes
Trial 3	Decline	Front	Tight	Hard	No
Trial 4	Incline	Back	Tight	Hard	No
Trial 5	Decline	Back	Tight	Soft	No
Trial 6	Incline	Front	Tight	Soft	No
Trial 7	Decline	Front	Tight	Soft	Yes
Trial 8	Incline	Back	Tight	Soft	Yes
Trial 9	Decline	Back	Loose	Soft	Yes
Trial 10	Incline	Front	Loose	Soft	Yes
Trial 11	Decline	Front	Loose	Soft	No
Trial 12	Incline	Back	Loose	Soft	No
Trial 13	Decline	Back	Loose	Hard	No
Trial 14	Incline	Front	Loose	Hard	No
Trial 15	Decline	Front	Loose	Hard	Yes
Trial 16	Incline	Back	Loose	Hard	Yes

V. RESULTS AND ANALYSIS

Since different factors were expressed differently in different subjects, the data was analyzed on a per-subject basis. For example, subject 1 used an in attaché of a small purse and hard shoes of high heels while subject 2 used an in attaché of a large briefcase and hard shoes of work boots. The time and frequency domain features listed in tables 2 and 3 were then calculated from the raw accelerometer data. Analysis consisted of a simple linear regression performed on each feature. In addition to the experimental factors A, B, C, D, and E, all possible interactions of the factors (AB, AC, AD, BCD, BC, BD, ACD, CD, ABD, ABC) were also considered. The regression model took the form of equation 3.

$$gaitFeature \sim 1\,(intercept) + ABCD + A + B + C + D + AB + AC + AD + BCD + BC + BD + ACD + CD + ABD + ABC$$

Equation 3 - Gait Feature Regression Model Equation

Table 6 shows our estimated coefficients and test results. The estimate column is a calculation representing about how much impact a factor or interaction of factors had on the response (or feature). The Standard Error (or SE) is "the standard deviation of the sampling distribution of a statistic" [15]. The test statistic (or tStat), is used to determine the probability of obtaining a certain result randomly from a certain population [8]. A p-value is the probability of obtaining the observed results when the null hypothesis is true [16]. For this experiment, the null hypothesis was that there would be no correlation between gait and the varying factors. P-values of < 0.05 were considered statistically significant for each factor or interaction of factors. Based on the p-values in the above example, the only factor to have an impact on this particular model for this particular feature of gait was D, hard versus soft shoes. Table 6 denotes all factors for all gait features determined to be statistically significant at the $p < 0.05$ level (denoted by *) and $p < 0.01$ level (denoted by **). Figure 11 is a plot of the linear best fit line for the response data, along with its 95% confidence intervals:

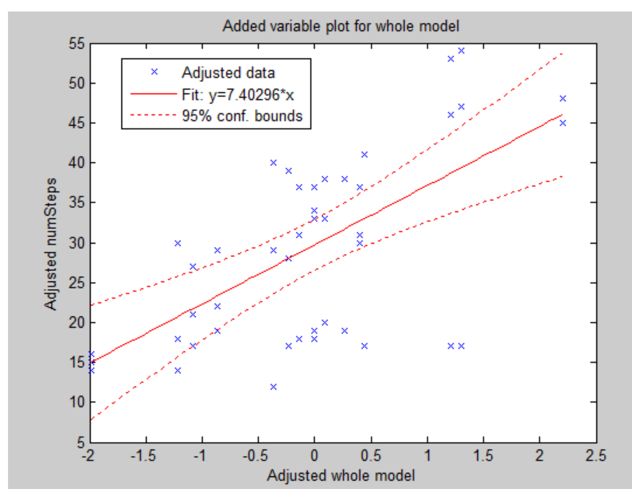

Figure 11 - Female Number of Steps Regression Model Plot

Since this experiment involved multiple repetitions, there was also a calculation of the variation of each feature between subjects and the within variation of each feature measured in the experiment. The between variation is a measure of the variation between similar trial runs with different subjects. The within variation is a measure of the variation between observations of each trial run within a specific set of experiment parameters.

TABLE 6 – TABLE OF STATISTICALLY SIGNIFICANT EXPERIMENTAL FACTORS FROM REGRESSION

Feature	Factor	Estimate	SE	tStat	p-value
No. of Steps –male	D	5.4583	1.571	3.4733	0.00149
No of Steps –male	E	-4.3542	1.571	-2.7707	0.00923
Step Length – Female	D	23.372	6.310	3.7036	0.00079
	CE	-14.445	6.310	-2.2891	0.02882
Step Length –Male	E	-19.237	6.399	-3.0063	0.00511
Step Time – Female	D	16.642	5.360	3.1046	0.00396
	AE	-13.177	5.360	-2.4582	0.01956
	CE	-14.346	5.360	-2.6762	0.01164
Step Time –Male	E	-16.16	7.689	-2.1017	0.04354
Average Power – Female	E	-2697.5	205.3	-	1.9367e-
	A	-584.76	205.3	-2.8483	0.00761
	B	518.39	205.3	2.525	0.01672
	C	-635.4	205.3	-3.095	0.00406
	D	422.7	205.3	2.0589	0.04771
	AD	726.08	205.3	3.5367	0.00126
	AE	885.92	205.3	4.3153	0.00014
	BC	-657.49	205.3	-3.2026	0.00307
	BE	-492.74	205.3	-2.4001	0.02238
	CE	910.96	205.3	4.4372	0.00010
Average Power – Male	E	-4256.3	473.4	-8.9894	2.8735e-
	A	-2320.2	473.4	-4.9003	2.6545e-
	B	3542	473.4	7.4806	1.6255e-
	C	-1579.2	473.4	-3.3352	0.00216
	BE	-2014.5	473.4	-4.2546	0.00017
Kurtosis –Female	E	-0.51935	0.162	-3.1988	0.00310
Kurtosis –Male	AD	-0.44098	0.187	-2.3496	0.02512
	CE	0.44098	0.187	2.3496	0.02512
Skewness –Female	E	-0.24938	0.049	-5.0248	1.8489e-
	AB	0.10551	0.049	2.126	0.04131
Skewness – Male	AD	-0.15223	0.059	-2.5502	0.01575
	CE	0.24593	0.059	4.1198	0.00024

In summary, the three features in the time-domain that produced statistically significant results under experimental conditions were 1) the number of steps taken, 2) the average step length, 3) and the average step time. The most impactful experimental factor for the female subject was the hard versus soft soled shoes (factor D). In each regression which returned results of a p-value less than 0.05, the factor that was involved was D. There were a few results where D and other factors (A, B, C) were interacting with each other; however, due to the Resolution V design confounding interactions of factors at the third level, the interaction of these other factors with D can be considered insignificant. By the hierarchy of significance, we are able to assume that the simplest explanation, D, is correct and had an impact on gait. Similarly, the most impactful experimental factor for the male subject was whether the phone was in attaché or not (factor E). Also, by the hierarchy of significance, we are able to assume that the factor ABCD, or E, was the simplest explanation on the impact of gait. Possibly the most exciting result here is that there was not an overwhelming response difference when factors were varied.

VI. CONCLUSION

Prior work has analyzed human gait data gathered from smartphone accelerometers to infer various health ailments. However, in most cases, the Smartphone was constrained to be affixed to a body part (hip or L3 region), which is not naturalistic. In this work, we utilized a factorial experiment to analyze the factors that affect human gait in naturalistic settings. We found that for our female subject, the most impactful factor was hard vs soft shoes. For the male subject, we found that the most impactful factor was whether the phone was in attaché or not. We were also able to verify that while significant, these factors did not affect gait analysis enough to invalidate results.

In addition to the factors we investigated, several other factors that may affect human gait are not considered in this experiment. A user's walk may change over time due to any number of circumstances including weather, phone placement, ground conditions or personal injury. A user's gait may also change if they are fatigued or in a bad mood. Ultimately, gathering more data to cover majority of relevant situations and labeling any contributing factors should improve inference accuracy.

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