ANALYSIS AND COMPARISON OF GAIT BETWEEN SUBJECTS WALKING VIA TREADMILL VERSUS GROUND

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Abstract
Gait patterns are linked to neurological features of the human body. Walking-related physical therapy after surgery or the onset of a disease often utilizes a treadmill to give the subject a controlled environment in which to exercise and relearn this skill. However, it has been found that noticeable differences exist in gait patterns on a treadmill with handrail support and on a flat, stationary surface[1]. The goal of this project is to measure gait patterns associated with surface and treadmill walking without support and analyze features associated with those patterns. A Cleveland Medical Devices BioRadio is connected to a goniometer via a wireless device. The goniometer is located at the hip with a Velcro belt and acquires the hip angle over time of each subject. BioRadio Capture Lite software is used to acquire and save the data. Previous investigators have shown that there are patterns of long range order present in human walking gait, and that these patterns change with age, disease, and disability. The calculations indicate that the fluctuation of the step duration of walking patterns show statistically significant differences between ground and treadmill data. These data suggest that treadmill walking may not appropriately mimic normal surface walking patterns in young, healthy adults.

1. Introduction

Gait describes the movement of limbs, or stance and swing phases, of a person or animal during locomotion. In physical therapy for those with trouble walking, a treadmill is commonly used as a safe, controllable environment in which a patient may relearn the skills necessary to move about in day-to-day life. It has been shown that noticeable differences exist in gait on a treadmill while the user holds onto support bars and on an immobile surface[1]. To further these past studies, the step durations (the time it takes a person to take a step with both feet) for walking on a flat surface and free-walking on a treadmill were recorded using five males and five females. Due to poor readings, two of the females' data were eliminated in this study. Next, each data series was subjected to three different analysis methods. Finally, results were grouped according to subject and walk type, and were statistically compared.

2. Methods

2.1 Subjects

This study investigates eight young, healthy subjects (five males and three females; average age 24 yr) that were instructed to walk eight minutes on the Texas Tech University track and eight minutes on a treadmill in the Neuro-Imaging Cognition Engineering (NICE) lab. The TTU track was chosen due to it being a level surface in order to compare level treadmill walking to. Each subject wore their own walking shoes for comfort.

To collect data, a Cleveland Medical Devices BioRadio was connected to a goniometer. The BioRadio wirelessly connected to the receiver via USB into the laptop and sampled at 256 Hz. The goniometer was attached on each subject's right hip via two Velcro belts, one around the waist and one around the upper thigh. This setup allowed for the researcher and subject to be independent while acquiring data, which prevented excessive interference with the subject's natural gait. While data was acquired on the track, the researcher walked behind each subject in order to not influence their walk. Subjects were instructed to not use the handrails on the treadmill.

Matlab was used to eliminate the first 30 seconds of each data set, along with the remaining data after 6.5 minutes. This prevented any starting or ending effects on the walk.

2.2 Step Duration

For each subject, the step duration was determined from the goniometer data. Step duration was used due to its prevalence in similar studies[1-3]. Before beginning the calculations, a 1024 Hz spline function was implemented to artificially increase the resolution of the data. Next, the step duration was calculated from determining a threshold value.

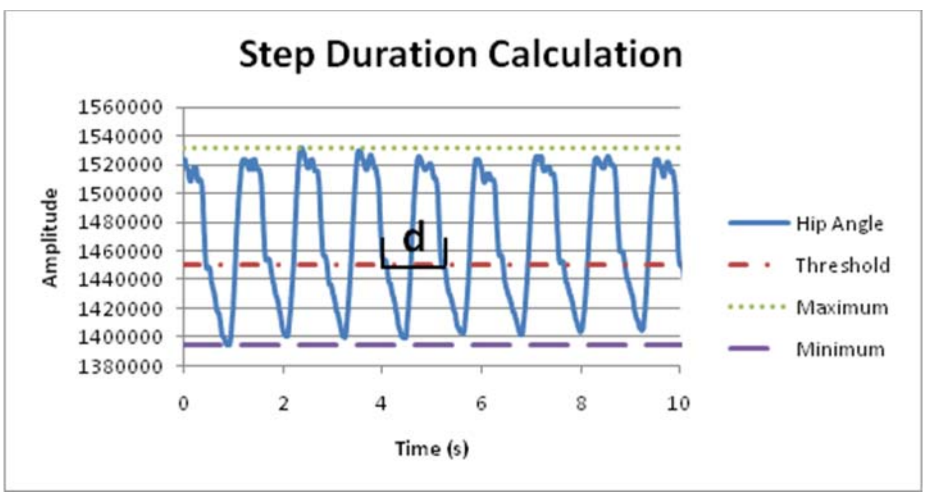

FIGURE 1: Typical step duration calculation where $threshold = [0.4 * (maximum - minimum)] + minimum$, where d is the duration for one step.

If a data sample crossed this threshold in one direction, a step was counted, and the step duration was calculated as the difference between the current step's time and the previous step's time. Then, it was appended to the step duration data. Most recorded goniometer data contained less noise near the bottom of the signal than the top due to the fact that some subjects failed to fully bend their knee. Thus, the threshold was calculated as 20-40% between the absolute minima and maxima, depending on the subject's particular data. This threshold change should not interfere with the calculations, assuming that the period changed mostly in time and less so in magnitude. Figure 1 shows the step duration calculation for one subject.

2.3 Smoothing

Though the step duration algorithm worked, noise in the recordings easily resulted in the miscalculation of steps. To mitigate this problem, the measurements could be filtered either during or after the ground/treadmill walks. For this study, the raw data was filtered after the data acquisition for each subject.

A central moving average is a very common and easy-to-implement way to smooth out problematic noise. Since leg length and walk speed can vary between subjects, it is important to base the range of data points to smooth on the number of samples per average step. If the noise-affected step duration transformation algorithm finds the median, then the value should remain very close to the actual average. This assumes that there is a normal distribution of step duration values (shown to be accurate later in the results) and an even distribution of false/missed steps in the data. After this, one may obtain the average number of samples per step by multiplying the average step duration by the sampling rate. Multiplying this number by a smoothing percentage **(**66% Subjects 1-5,7 and 10% for Subject 6) will result in a smoothing amount.

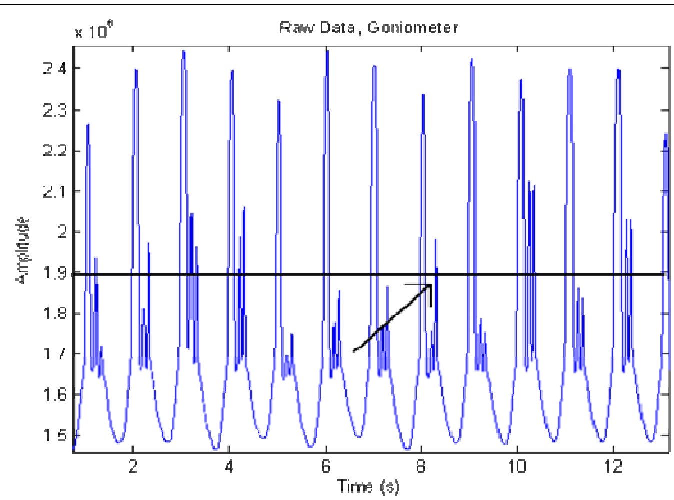

FIGURE 2: Example of raw goniometer data where noise is causing the miscalculation of steps.

A central moving average is not perfect. With a walk pattern too erratic or noisy, an abundance of false steps will prevent an accurate smoothing amount and could ruin any analyses using the data.

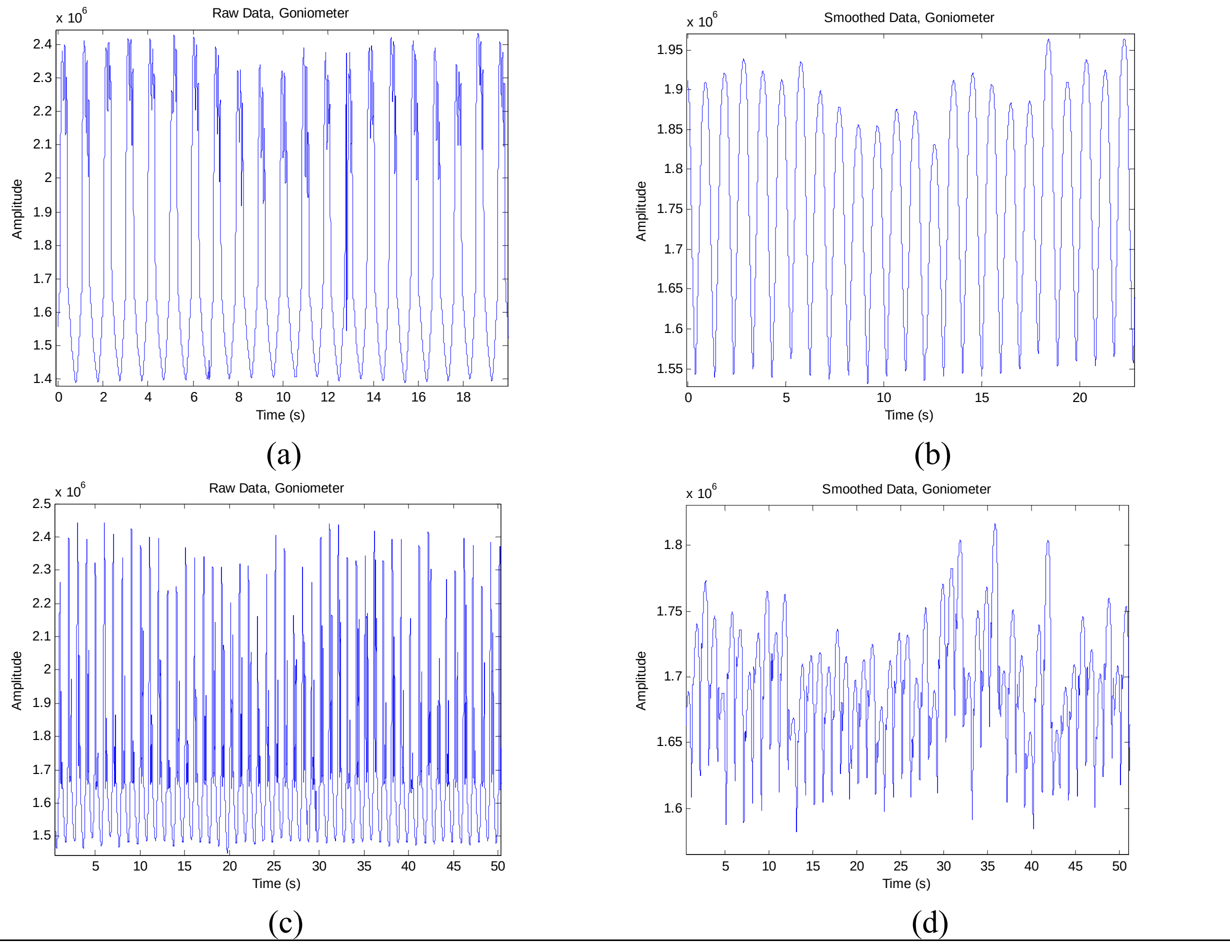

FIGURE 3: (a) Raw goniometer data before smoothing for subject 10. (b) Data after smoothing is applied for subject 1. (c) Raw goniometer data before smoothing for subject 6. (d) Data after smoothing is applied for subject 6; note that smoothing, in this case, makes the data unusable.

3. Analysis

Based on common tests, three forms of analysis were used: a histogram, detrended fluctuation analysis, and central moving average fluctuation analysis.

3.1 Histogram

A histogram was the first analysis method implemented in order to gain a qualitative overview of the data. The maximum and minimum elements in the step duration data were found, and ten evenly-sized intervals were chosen according to the number of intervals predefined in the program. For each element in the step duration data, the element was checked to see which interval it fit within; that particular interval's counter was increased by one. The elements were sorted according to an interval, the integers were divided by the total number of elements, and the frequencies were graphed.

3.2 Detrended Fluctuation Analysis (DFA)

Detrended Fluctuation Analysis, or DFA, is based on a classic-root-mean-square analysis of a random walk or Brownian motion[4]. It is employed to determine the self-affinity (long-term correlation of a signal with itself) of a signal. This method is useful because it reduces noise effects and removes local trends. It is implemented frequently in gait analysis due to the partially non-stationary (changing in probability distribution, mean, etc. over time) nature of gait and its success with other physiological data series[5]. DFA1 was chosen because it uses simple linear detrending.

To perform this analysis, data were truncated at the highest possible power of two. This was useful due to the large number of factors that were produced. Consequently, this increased the accuracy of fluctuation coefficient calculations. Next, the truncated step duration data, x_i, were transformed via the function

$$X[t] = \sum_{i=1}^{t} (x_i - \langle x_i \rangle). \tag{1}$$

That is, each element in $X[t]$ is the cumulative deviation from x_i's mean of all the elements up to and including t. $X[t]$ starts from zero and returns to zero at its ends because the summation of the difference from the mean of any data series is equal to zero.

After this, $X[t]$ was divided into boxes of equal size multiple times, starting at box size n =16 and ending with the number of elements, counting by powers of 2. For every value of n, each individual box was detrended (had a linear best-fit line subtracted from it), and the fluctuation $F(n)$ was calculated with

$$F(n) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \mathcal{X}[i]^2} \tag{2}$$

where $\mathcal{X}[i]$ is the detrended $X[t]$, and N is the number of elements in $X[t]$ (which is also equal to n times the number of boxes). Once this was done for every box size, the results were plotted on a log-log graph of box size vs. fluctuation (Figure 4).

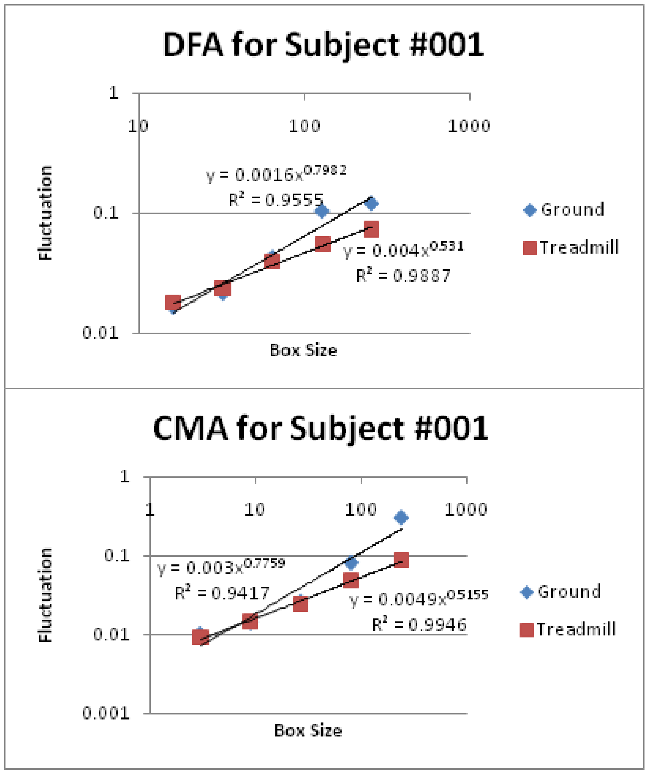

FIGURE 4: DFA and CMA log-log plotting for subject 1.
The fluctuation is higher for ground walking than treadmill walking for this particular subject.

Finally, a best fit exponential (an^{α}) was found for the box size vs. fluctuation graph via a least-squares best fit approximation. The fluctuation exponent α quantifies the self-affinity of the signal. Values less than 0.5 are anti-correlated, values around 0.5 indicate non-correlation, and values above 0.5 indicate correlation, which healthy, normal walks should be. A higher α value represents a higher level of correlation.

3.3 Central Moving Average Fluctuation Analysis (CMA)

The central moving average analysis shares many qualities with DFA. Like DFA, it results in a fluctuation exponent which represents correlation. Unlike DFA, $\mathcal{X}[i]$ comes from a linear detrend of a moving window rather than a stationary one. CMA is valued for this quality since abrupt jumps between DFA's neighboring segments caused by detrending may be detrimental to the accuracy of results[2,4]. The only change with regards to calculation is demonstrated in the calculation of $\mathcal{X}[i]$:

$$\mathcal{X}[i] = X[i] - \frac{1}{N} \sum_{k=-(\frac{n-1}{2})}^{\frac{n-1}{2}} X[i+k]. \tag{3}$$

Again, n is box size. Note that n is an odd number ($\frac{n-1}{2}$ must be an integer), so powers of 3 are used for each fluctuation calculation. Additionally, the moving detrend would go out of bounds at the start and end of $X[i]$ using this equation, so it was assumed that this data would repeat itself given the same conditions. Thus, the end of the data returns to the beginning and vice-versa.

4. Results

Histograms tend to resemble normal distributions. However, they all include a slight shift to the left or right. This is most likely caused by an outlier on one side of the other, thus these graphs fit within expectations.

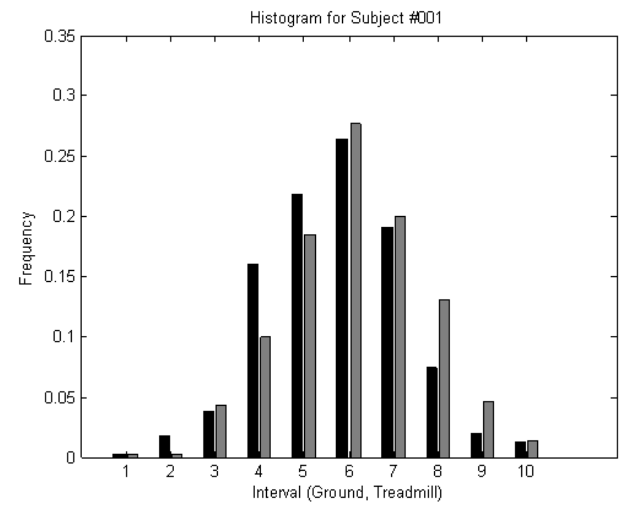

FIGURE 5: Histogram for a subject's stride interval comparing ground (black) and treadmill (gray).

DFA and CMA data were analyzed using single-mean student's t-tests, first via the ratio of DFA's α to CMA's α, then via the difference between the two. The t-tests were performed in this fashion as opposed to two-mean t-tests because the latter method fails to preserve the pairing of subjects' fluctuation coefficients. Null hypothesis for average results was $\mu = 1$ for ratio analysis and $\mu = 0$ for difference analysis. Alternate hypothesis was $\mu > 1$ for ratio analysis and $\mu > 0$ for difference analysis.

		#001	**#002**	**#003**	**#004**	**#005**	**#006**	**#007**	**#008**
DFA	<u>Ground</u>	0.9352	0.7569	0.959	0.8028	0.508	0.554	1.08	0.7982
	<u>Tread</u>	0.4682	0.5638	0.5382	0.7358	0.8643	0.8394	1.0004	0.531
CMA	<u>Ground</u>	0.9126	0.822	0.7407	0.7072	0.5985	0.4685	1.1334	0.7759
	<u>Tread</u>	0.5975	0.4544	0.6446	0.682	0.7443	0.4408	0.9096	0.5155

TABLE 1 - Fluctuation Coefficients (α). Usually these values are higher for ground walking than treadmill walking.

From the fluctuation coefficients, one may calculate the level of significance:

		$\bar{X}$	S	t_2	α_2
$\alpha_{ground}/\alpha_{tread}$	**DFA**	1.255423	0.500707	1.442848	0.096321
	CMA	1.267564	0.325456	2.325306	0.026521
$\alpha_{ground} - \alpha_{tread}$	**DFA**	0.106625	0.300505	1.003581	0.17474
	CMA	0.146263	0.174465	2.371211	0.024785

TABLE 2 – Mean of Samples, Sample Standard Deviation, *t*, and Level of Significance

$\bar{X}$ represents the sample mean, and S represents sample standard deviation. The level of significance, calculated using t_2, is given by

$$t_2 = \frac{\bar{X} - \mu_0}{S - \sqrt{n}}. \tag{4}$$

Again the number of samples is n. To find this level of significance, one must calculate the area under the probability density function of the student's t distribution, which is

$$f(t) = \frac{\Gamma\left(\frac{n}{2}\right)}{\sqrt{(n-1)\pi}\,\Gamma\left(\frac{n-1}{2}\right)}\left(1 + \frac{t^2}{n \quad 1}\right)^{-\left(\frac{n}{2}\right)}, \tag{5}$$

from $t = t_2$ to $t = \infty$ in the case of these null/alternate hypotheses.

This task can be performed in a simple manner using a Matlab function, which calculates $f(t)$ from 0 to 30 in increments of 0.001. By summing the values from $f(t_2) * 0.001$ to $f(30) * 0.001$, α_2 can be closely approximated (with slight overestimation).

In both cases, the sample standard deviation and level of significance found from CMA's results were much lower than that of DFA's results. This may imply that CMA yields more accurate figures than DFA and, with very low α_2's of 2.65% and 2.48%, that ground gait and treadmill gait are different enough to merit a change in treadmill-related physical therapy. Otherwise, treadmill practice may leave patients unable to cope with an imperfect walking environment.

5. Conclusion

In summary, this study met its primary goals of proof of concept and ground/treadmill comparisons. The analysis itself yielded a statistically significant difference between ground gait and free-walking treadmill gait; this contradicts an assertion found in another source[1]. This find is interesting because it, if true, suggests that treadmill-intensive physical therapy may not sufficiently teach a patient how to properly walk on and react to the imperfections in the ground beneath their feet.

References

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