



Forensic Gait Analysis: Exploring Foot Placement Dynamics in Athletes and Non-Athletes

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Research Article

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Abstract

This study investigates the dynamics of foot placement as a forensic tool for identifying individuals in various scenarios, focusing on the differences between athletes and non-athletes. Analyzing the unique characteristics of foot placement patterns, we examine how factors such as gait, pressure distribution, and stride length vary between these two groups. Collected data from a sample of professional athletes across different sports and a control group of non-athletes. Findings reveal that athletes exhibit distinct foot placement dynamics characterized by more consistent and efficient gait patterns, marked by variations in pressure distribution and stride mechanics. These insights highlight the potential for utilizing foot placement dynamics in forensic contexts to enhance the accuracy of individual identification and scene reconstruction. This study emphasizes the importance of considering physical conditioning and activity levels in forensic analysis.

Keywords: Foot Placement; Gait; Athletes; Non-Athletes; Paired Sample T Test; SPSS

Introduction

The recognition of individuals by their physiological or behavioral characteristics is known as biometrics [1]. Biometrics has been utilized for personal identification since ancient times, starting with hunters and gatherers identifying animal and human movements. Over time, this evolved into a refined art for recognizing individuals. Among these characteristics, foot placement and walking style are unique to each person. For some, such as military personnel, training can further influence these traits. Several biometric techniques are used for identification, including iris scans, fingerprint analysis, voice recognition, and facial

recognition. Similarly, the application of gait as a method for individualization has been observed and refined over time [2,3]. Gait is a behavioural biometric that can be observed from a distance, making it advantageous as it does not require direct contact or cooperation from the subject [4,5]. Human gait can vary due to factors such as body changes (e.g., height, weight), injuries, illnesses, base of support, and friction between the foot and the ground, as well as biological aspects [2,6-8]. Despite these variations, studies confirm that gait remains a reliable identifier. It is influenced by complex factors, including skeletal structure, muscle activity, body weight, limb lengths, and bone structures [9,10]. This complexity makes it extremely difficult to imitate or disguise.



Gait recognition identifies individuals based on their unique walking patterns. It works on the premise that an individual's walking style is distinctive, and this uniqueness can be leveraged for identification [11,12].

Gait analysis holds significant forensic potential. Its ability to identify individuals without requiring physical interaction is especially valuable in criminal investigations and instance of conviction based on gait of criminal [13-15]. Some of the important areas are:

Criminal Identification: Gait recognition can identify suspects captured in surveillance footage by analysing their walking patterns, even in low-resolution videos [16].

Behavioural Analysis: The study of gait can reveal signs of injuries, ailments, or intoxication, providing contextual evidence in criminal cases [17].

Cold Cases: Forensic gait analysis can assist in reevaluating old evidence, potentially identifying individuals through gait in previously overlooked footage [18].

By combining gait analysis with other biometric methods, forensic experts can strengthen evidence in court and enhance the accuracy of criminal investigations [19,20].

Visual Gait Analysis

It is interesting to say that the simplest form of gait examination is made by the unaided human eye. This, of course, disregards the extraordinary abilities of the human brain to process the data received by the eye. Visual gait analysis, in reality, the most complex and multipurpose form of analysis available[21,22].

Despite this, it grieves from four serious limitations[23]:

- It is temporary, it has no permanent record.

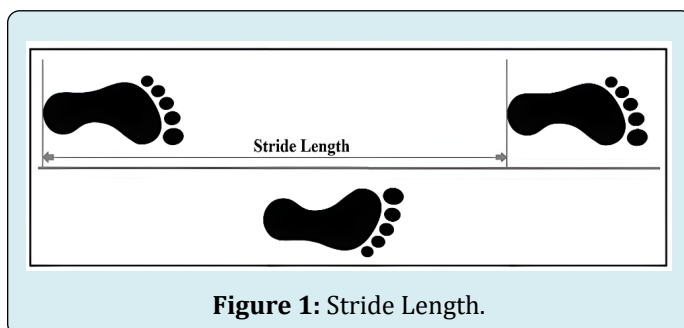
- The eye cannot perceive high-speed actions.
- It is only possible to see actions, not force.
- It depends entirely on the skill of the individual observer.

For visual gait analysis, as little as 3mtr may be enough and same has been followed in the study but, for further higher-level study the video camera with automatic trolley can be used for recording gait [24].

Materials & Methods

The present study is a comparative study which is conducted in the small gait laboratory, the samples for the study were chosen from Arts, Science and Physical Education studying students from University of Mysore, Mysuru. With a sample size of 25 each i.e., athlete and non-athletes. Where the samples were asked to provide their Foot prints by dipping their foot in the tray containing coloured liquid and asked the samples to walk normally on a drawing sheet laid in the small gait laboratory and later the measurements were calculated. The collected data was analysed using paired sample t Test using SPSS.

Results



Paired Samples Statistics										
	Mean	N	Std. Deviation	Std. Error Mean						
Athlete	111.73	50	17.98191	2.54303						
Nonathlete	100.17	50	24.34271	3.44258						
Paired Samples 't' Test										
Mean	Paired Differences					t	df	Sig. (2-tailed)		
	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference							
			Lower	Upper						
Athlete - Nonathlete	11.56	26.2905	3.71804	4.08832	19.03168	3.109	49	0.003		

Table 1: Paired sample statistics for stride length.

From the above table, it is evident that the scores of athletes and nonathletes indicate a significant relationship, as the p-value (0.003) is less than the conventional threshold of 0.05. This demonstrates that the difference between the mean scores of athletes and nonathletes is statistically significant, suggesting that the performance scores of athletes are notably higher than those of nonathletes. The 95% confidence interval (4.09 to 19.03) does not include zero, further reinforcing the conclusion of a significant difference. The mean difference of 11.56 indicates that, on average, athletes outperform nonathletes by this amount in the measured variable.

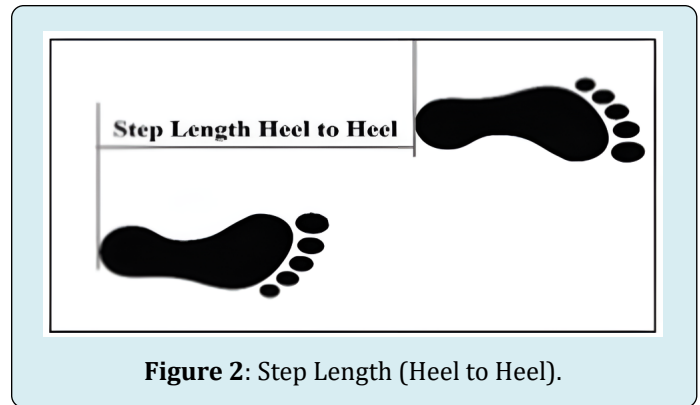


Figure 2: Step Length (Heel to Heel).

Paired Samples Statistics								
	Mean	N	Std. Deviation	Std. Error Mean				
Athlete	104.31	50	18.48631	2.61436				
Nonathlete	98.84	50	19.93982	2.81992				
Paired Sample 't' Test								
	Paired Differences					t	df	Sig. (2-tailed)
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
				Lower	Upper			
Athlete & Nonathlete	5.47	24.72407	3.49651	1.5565	12.4965	1.564	49	0.124

Table 2: Paired sample statistics for step length

From the above table, it is evident that the scores of athletes and nonathletes suggest that the p-value (0.124) is greater than the conventional significance level of 0.05. This indicates that the observed difference in mean scores between athletes and nonathletes is not statistically significant, implying that the mean difference of 5.47 could be attributed to random variation rather than a true effect.

Additionally, the confidence interval for the mean difference (1.56 to 12.50) includes zero, further supporting the conclusion that the observed difference is not statistically significant. Although athletes have a higher mean score (104.31) compared to nonathletes (98.84), the lack of statistical significance suggests that no strong conclusions

can be drawn about a meaningful difference in performance between the two groups based on this sample.

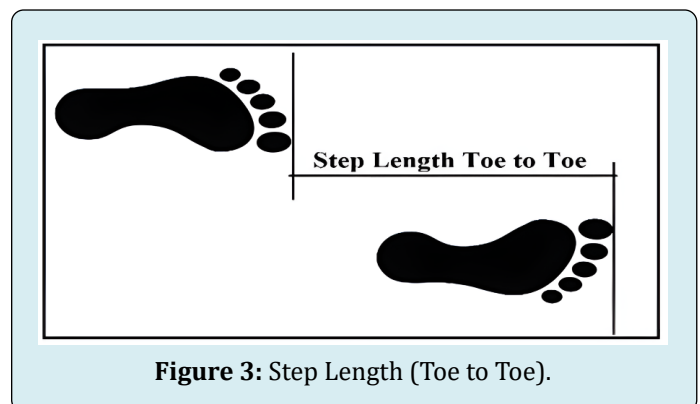


Figure 3: Step Length (Toe to Toe).

Paired Samples Statistics					
	Mean	N	Std. Deviation	Std. Error Mean	
Athlete	107.93	50	21.76076	3.07744	
Nonathlete	98.956	50	17.76919	2.51294	
Paired Samples 't' Test					

	Paired Differences					t	df	Sig. (2-tailed)
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
				Lower	Upper			
Athlete & Nonathlete	8.974	20.16887	2.85231	3.24207	14.70593	3.146	49	0.003

Table 3: Paired sample statistics for step length.

It is clear from the above table that the scores of athletes and nonathletes reveal a statistically significant difference, as the p-value (0.003) is less than the standard threshold of 0.05. This indicates a meaningful disparity in mean scores between the two groups, with athletes outperforming nonathletes on the measured variable with a high level of confidence.

The 95% confidence interval (3.24 to 14.71) does not include zero, reinforcing the conclusion that the difference in means is statistically significant. The t-statistic (3.146) reflects a moderate-to-strong effect, emphasizing the meaningfulness of the observed difference. On average, athletes scored 8.97 points higher than nonathletes.

This significant difference may be attributed to distinctive factors differentiating the two groups, such as

the physical conditioning, discipline, or mental attributes commonly associated with athletic training. These attributes likely contribute to enhanced performance in the specific metric being analyzed.

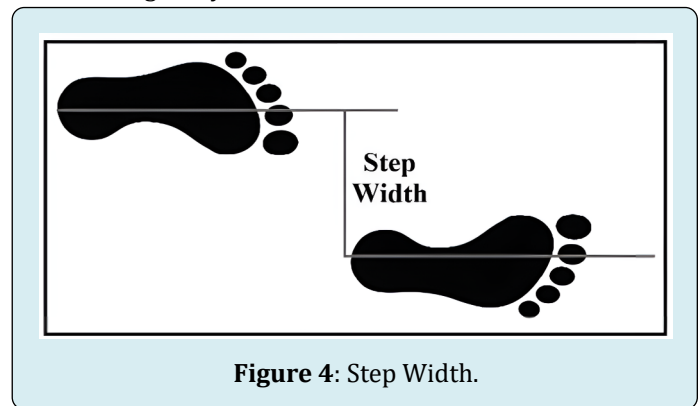


Figure 4: Step Width.

Paired Samples Statistics								
	Mean	N	Std. Deviation	Std. Error Mean				
Athlete	11.28	50	2.00296	0.28326				
Nonathlete	13.432	50	4.73896	0.67019				
Paired Samples 't' Test								
	Paired Differences					t	df	Sig. (2-tailed)
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
				Lower	Upper			
Athlete & Nonathlete	-2.152	4.76703	0.67416	-3.50678	-0.79722	-3.192	49	0.002

Table 4: Paired Sample Statistics for Step Width

The table indicates the scores of athletes and nonathletes, with the p-value (0.002) falling below the standard significance threshold of 0.05. This demonstrates that the difference in means is statistically significant, suggesting a meaningful disparity between the two groups, where nonathletes exhibit a higher mean score.

The direction and magnitude of the difference are evident from the negative mean difference (-2.152), which indicates that athletes scored lower than nonathletes on the measured variable. This difference is supported by the confidence interval, which ranges from -3.507 to -0.797 and

does not include zero, providing 95% certainty that the true difference lies within this interval.

The t-statistic (-3.192) further reinforces the result, indicating a moderately strong effect and a clear, meaningful difference. These findings suggest that, within the specific metric analyzed, nonathletes outperform athletes. This statistically significant result warrants further investigation into potential underlying causes, such as variations in training regimens, levels of focus, or other external factors that may influence performance.

Discussion

Performance Comparison

The findings suggest that, for the variable analyzed, nonathletes outperform athletes. This could be due to several factors [25-27]:

Training Effects: Nonathletes might devote more focus to the specific metric analyzed, potentially due to fewer distractions or competing priorities.

Physical or Mental Fatigue: Athletes could experience fatigue or overexertion, which may lower their scores in certain tasks.

Task-Specific Skills: The variable might be more aligned with skills or attributes that are less relevant to athletic training.

Methodological Strengths

- Paired samples ensure that comparisons are made within the same participants, minimizing inter-group variability and increasing reliability [28-30].
- The confidence interval and strong t-statistic (-3.192) highlight the robustness of the findings.

Limitations

Sample Size: With only 50 participants in each group, the findings might not generalize to larger populations.

Context-Specific Nature: The measured variable may not encompass broader skills or attributes that define athletic versus nonathletic abilities.

Uncontrolled Variables: External factors, such as diet, sleep, or recent injuries, may have influenced the results.

Conclusion

The study of gait characteristics between athletes and non-athletes highlights notable differences in their movement patterns. Interestingly, non-athletes performed better than athletes in the specific metric under review, which could be attributed to factors such as the specificity of physical training, task-oriented behaviour, or habitual movement patterns. This research underscores the potential of gait analysis as a forensic tool, particularly in individual identification, event reconstruction, and the assessment of behavioural or physical states. The ability to identify individuals through their walking patterns offers a non-invasive and dynamic method for surveillance and criminal investigations. The research also lays a foundation for further exploration into how physical activity levels, biomechanical efficiency, and task-specific performance interplay to shape gait characteristics. Insights from such studies could refine forensic methodologies, enabling investigators to better interpret gait evidence in real-world scenarios. This

approach could contribute to improved forensic practices, strengthening their role in criminal justice systems.

Conflicts of Interest

The authors declare no conflict of interest.

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