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# Non-invasive, spatio-temporal gait analysis for sprint running using a single camera

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**Abstract**

Sprint running velocity is the product of step length and step rate. A tool to measure these key metrics would aid sprint training. Athletes require fast and non-invasive analysis tools, to allow them to focus on performance. A non-invasive, single camera gait analysis system (Gait Analyser) was developed and installed at the Sheffield Hallam University City Athletics Stadium (SHUCAS). The Gait Analyser filmed athletes sprinting in lanes 1, 5 and 8 wearing different coloured shoes in varied lighting conditions (e.g. sunlight or overcast). The Gait Analyser automatically identified the position and time of athlete's foot contacts, allowing the calculation of step length, step time and step velocity. Output data were compared to corresponding, manually identified measurements. For optimised setups, 100% of foot contacts were identified. Resultant direction root-mean square error (RMSE) for foot contact position and time was 108.9 mm and 0.03 s respectively. RMSE for step length, step time and step velocity was 4.9 mm, 0.00 s and 0.07 m·s$^{-1}$ respectively. The Gait Analyser measured spatio-temporal gait parameters of sprint running *in situ* without applying markers or sensors to the athlete or the running track: results were available 2-3 s after capture.

## 1. Introduction

Gait analysis has many applications, including athletic performance analysis, clinical analysis and biometrics [1]. However in athletics, the use of instruments (i.e. markers or sensors) for direct measurement can be impracticable.

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Sprint running velocity is the product of step length and step rate [2]. To improve sprint velocity, one or both must be improved. The ability to measure and subsequently monitor these key metrics would aid sprint training. When in training, athletes require fast and non-invasive analysis tools; this allows athletes to focus on performance and be unperturbed by the presence of equipment. However, no commercial tool – which performs fast and non-invasive analyses of sprint running gait – is currently available.

Markerless, video-based measurements of spatio-temporal gait parameters – such as step length and step time – can be achieved by the identification of foot contacts. Bouchrika and Nixon [3] presented a single camera method for identifying foot contacts and reported identification accuracy of 0.52% of participant height. However, temporal data were removed. This reflected the sequential accumulation of image data to allow the spatial identification of foot contacts. Jung and Nixon [4] presented a single camera method for the spatial identification of foot contacts during walking. The authors used a gait trajectory model (vertical oscillation) to retrieve spatio-temporal information of foot contacts. For walking in a calibrated, biometric tunnel, Jung and Nixon [4] reported that 95.6% of foot contacts were identified within ± 100 mm of ground truth data. However, temporal data were not assessed.

Both approaches [3,4] rely on the accumulation of image information (accumulator maps) to identify foot contacts; this is computationally exhaustive and limits their application when developing performance analysis tools. Dunn et al. [5] presented a markerless, spatio-temporal gait analysis system. The system was view- and gait-independent, allowing the analysis of single camera images of multi-modal gait (i.e. walking and running). Dunn et al. [5] reported that the system identified 99.6% of foot contacts during walking and running (four camera perspectives); RMSE (resultant direction) was 52.2 and 103.4 mm for shod walking and shod running respectively. The system also quantified spatio-temporal gait parameters for 91.3% of trials [5]. Importantly, it was noted that image processing ($0.87 \pm 0.05$ s per image) could be applied to an image stream (i.e. network camera) [5].

Recently, the system presented by Dunn et al. [5] has been developed for the purpose of athletic performance analysis (hereafter Gait Analyser). The Gait Analyser – developed using the .NET framework (C#) – automatically analyses images (live camera stream or memory) to identify foot contacts; multithreading is exploited to allow parallel image processing. The Gait Analyser reconstructs the real world position and time of foot contacts, allowing the calculation of spatio-temporal gait parameters. Results are fed back to the user in numeric and, if opted, visual formats (e.g. analysis image and video). The purpose of this study was to validate spatio-temporal gait parameters measured by the Gait Analyser *in situ* (i.e. SHUCAS 100 m running track) and assess sprint performance.

## 2. Method

### 2.1. Participants

Three male and two female athletes (age = $26.6 \pm 5.7$ years; stature = $1.77 \pm 0.14$ m; mass = $72.9 \pm 20.0$ kg) were recruited. Athletes were briefed to aid the completion of tasks; written informed consent was obtained. Approval for all procedures was obtained from the Research Ethics Committee of the Faculty of Health and Wellbeing, Sheffield Hallam University. Athletes performed five maximal effort 10 m sprints, in lanes 1, 5 and 8 of the SHUCAS running track (Figure 1), with up to 10 minutes recovery. Athletes wore their own shoes; shoes were different colour, size (UK 5 – 10) and type (Figure 1). No markers, sensors or other instrument was applied to athletes or the track.



Fig. 1. Camera view (zoomed-in) of the running track with global coordinate systems highlighted (left) and running shoes (right) of different type, size and colour, worn by athletes 1 – 5 (top to bottom respectively).

## 2.2. Gait Analyser

The Gait Analyser was designed to be quick and easy to use. To perform analyses, users are only required to identify the running track lane and capture duration. A fixed network camera (AXIS Q1615-E, Axis Communications, Sweeden), viewing the final 10 m of the 100 m straight (perpendicular to running direction), streams RGB colour images (1280 × 720 pixels) to a server computer at 50 Hz. The Gait Analyser software – operated using a graphical user-interface – allows analyses to be conducted over a wireless local area network (i.e. Wi-Fi) using WiFi enabled devices (i.e. laptop, tablet, etc.). This minimises restrictions to the system's use (i.e. portability). Following initialisation, the Gait Analyser processes image streams (live camera stream or memory) to identify foot contacts. Intrinsic and extrinsic camera parameters are retrieved from a database (Microsoft SQL Server 2014, Microsoft Corporation, Redmond, US) to perform single camera calibration, allowing position reconstruction [6]. The Gait Analyser reconstructs real world position and time of foot contacts, allowing the system to calculate spatio-temporal gait parameters. Figure 2 illustrates an analysis image provided by the Gait Analyser.
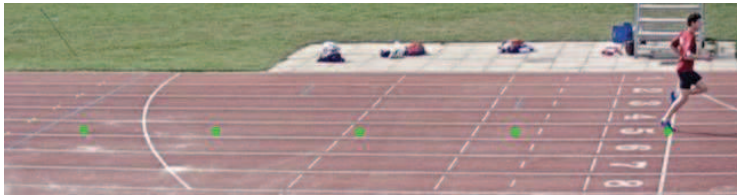


Fig. 2. Example analysis image exported by the Gait Analyser (foot contacts visualised by green circles).

## 2.3. Validation

Foot contacts were manually identified at a sub-pixel resolution using *Check2D* (Centre for Sports Engineering Research, Sheffield, UK). The time and location of foot contacts were subjectively identified (perceived location of peak force application at mid-stance) for all foot contacts inside lane markings. Foot contacts (n = 65) for three image sequences (lanes 1, 5 and 8) were identified on five occasions: standard error of the mean was ≤ 0.35 pixels or ≤ 15.9 mm (resultant direction) and < 0.01 seconds for all foot contacts. To allow direct comparison to manually identified data, the image coordinates and time of foot contacts identified by the Gait Analyser were exported following each trial. To reconstruct the position of image coordinates [6], single camera calibration was performed. Intrinsic camera parameters were calculated by filming a 6 × 6 checkerboard of 30 mm squares held in different positions and orientations relative to the camera. Checkerboard corners were extracted and processed using *Check2D*. Track line intersections of lanes 1, 5 and 8 were manually identified at a sub-pixel resolution. Intersection coordinates were identified on five occasions: standard error of the mean was ≤ 0.20 pixels or ≤ 9.1 mm (resultant direction) for all coordinates. The mean intersection coordinates for each lane were used to calculate corresponding extrinsic camera parameters; *X* and *Y* axes represent lane width and length respectively (e.g. Figure 1).

For sequential foot contacts, step length (mm), step time (s) and step velocity (m·s$^{-1}$) were quantified. Step length and step time were defined as the absolute difference between contralateral foot contact location and time respectively. Step velocity was defined as the quotient of step length and step time. Finally, the time duration to perform gait analyses was recorded. Agreement was assessed using Bland and Altman 95% limits of agreement (LOA). In the case of heteroscedastic data distribution, i.e. $|r^2| > 0.1$, ratio LOA (dimensionless) was also reported. Further, root-mean square error (RMSE) was calculated with the following:

$$RMSE = \sqrt{\sum_{i-1}^{N}(X_{iR} - X_{ir})^2 / N} \tag{1}$$

where $X_{iR}$ is the criterion, $X_{ir}$ is the estimate and *N* is the number of data points.

## 3. Results

Results are presented in three parts. Sub-section 3.1 presents foot contact identification using a generic setup. Sub-section 3.2 presents foot contact identification, agreement limits, measurement error and analysis times using optimised setups. Sub-section 3.3 presents an assessment of sprint performance using data derived by Gait Analyser.

### 3.1. Generic system setup

Table 1 presents foot contacts identified by the Gait Analyser (true positive: $T_P$), incorrectly identified (false positive: $F_P$) and incorrectly rejected (false negative: $F_N$) foot contacts. Using a generic system setup, the Gait Analyser identified 344 of 350 (98.3%) foot contacts ($T_P$: Table 1). The Gait Analyser incorrectly identified 12 foot contacts ($F_P$: Table 1) and incorrectly rejected 5 foot contacts ($F_N$: Table 1). False positive and false negative foot contacts were only observed for Athlete 2 (Table 1).

Table 1. Foot contact identification and error types using a generic system setup.

|  | Athlete 1 | | | Athlete 2 | | | Athlete 3 | | | Athlete 4 | | | Athlete 5 | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | L1 | L5 | L8 | L1 | L5 | L8 | L1 | L5 | L8 | L1 | L5 | L8 | L1 | L5 | L8 |
| Foot contacts | 21 | 24 | 21 | 25 | 25 | 25 | 21 | 20 | 22 | 26 | 25 | 25 | 23 | 24 | 23 |
| $T_P$ | 21 | 24 | 21 | 19 | 25 | 25 | 21 | 20 | 22 | 26 | 25 | 25 | 23 | 24 | 23 |
| $F_P$ | 0 | 0 | 0 | 9 | 2 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| $F_N$ | 0 | 0 | 0 | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

### 3.2. Optimised system setups

Table 2 presents foot contacts identified by the Gait Analyser using optimised system setups. The generic system setup (sub-section 3.1) and two additional system setups (higher and lower image segmentation thresholds) constitute optimised system setups. Using these setups, the Gait Analyser identified 350 of 350 (100%) foot contacts ($T_P$: Table 2). No foot contacts were incorrectly identified ($F_P$: Table 2) or incorrectly rejected ($F_N$: Table 2).

Table 2. Foot contact identification and error types using an optimised system setup.

|  | Athlete 1 | | | Athlete 2 | | | Athlete 3 | | | Athlete 4 | | | Athlete 5 | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | L1 | L5 | L8 | L1 | L5 | L8 | L1 | L5 | L8 | L1 | L5 | L8 | L1 | L5 | L8 |
| Foot contacts | 21 | 24 | 21 | 25 | 25 | 25 | 21 | 20 | 22 | 26 | 25 | 25 | 23 | 24 | 23 |
| $T_P$ | 21 | 24 | 21 | 25 | 25 | 25 | 21 | 20 | 22 | 26 | 25 | 25 | 23 | 24 | 23 |
| $F_P$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| $F_N$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Position errors in the $X$ direction constituted the largest component of $R$ direction (resultant of $X$ and $Y$ directions) position errors (Table 3). Position errors in the $X$ direction were heteroscedastic (Table 3); 95% of ratios were between 93% of the mean ratio. Foot contact time ($T$) was identified after the perceived instant of mid-stance (Table 3). Further, contact time errors were heteroscedastic; 95% of ratios were between 8% of the mean ratio.

Table 3. LOA (absolute and ratio) and RMSE for foot contact position ($X$, $Y$ and $R$ directions), foot contact time ($T$), step length ($SL$), step time ($ST$) and step velocity ($SV$).

|  |  | Absolute LOA | $|r^2|$ | Ratio LOA | RMSE |
| --- | --- | --- | --- | --- | --- |
|  | $X$ (mm) | 48.8 ± 232.9 | 0.22 | 1.13 (×/÷ 2.07) | 48.8 |
| Foot contact position | $Y$ (mm) | 44.4 ± 119.7 | 0.08 | - | 44.4 |
| (n = 350) | $R$ (mm) | - | - | - | 108.9 |
|  | $T$ (s) | -0.03 ± 0.03 | 0.15 | 0.96 (×/÷ 1.05) | 0.03 |
| Step parameters | $SL$ (mm) | -4.9 ± 177.7 | 0.09 | - | 4.9 |
| (n = 275) | $ST$ (s) | 0.00 ± 0.03 | 0.08 | - | 0.00 |
|  | $SV$ (m·s$^{-1}$) | -0.07 ± 1.18 | 0.11 | 0.99 (×/÷ 1.16) | 0.07 |

For step parameters, 95% LOA were -4.9 ± 177.7 mm and 0.00 ± 0.03 s for step length (*SL*) and step time (*ST*) respectively (Table 3): *SL* estimates were systematically shorter and *ST* estimates similar. *SL* and *ST* differences did not increase in relation to mean values; error distributions were homoscedastic. Step velocity (*SV*) differences were heteroscedastic (Table 3); 95% of ratios were between 17% of the mean ratio. Finally, the time to provide numeric results (capture completion to numeric results: $A_{T1}$) was 1.6 ± 1.0 s. The time to provide visualised results (capture completion to visualisation: $A_{T2}$) was 1.9 ± 1.0 s. Image analysis time corresponded to 0.03 ± 0.01 s (36.5 Hz).

### 3.3. Performance analysis

Sprint velocity (derived from *SV*) for all five athletes was 8.1 ± 0.9 m·s⁻¹. Sprint velocity ranged between 6.2 to 10.3 m·s⁻¹. Figure 3 illustrates the relationship between step length and step rate ($r^2 = -0.29$) for each sprint (each coloured circle) for individual athletes (each colour); best performances are highlighted by a star. Athletes 1 and 3 used similar step strategies (Figure 3) to achieve similar maximum sprint velocities (10.2 and 10.3 m·s⁻¹ respectively). Athlete 2 used a step strategy that comprised of a comparatively high step rate and short step length (Figure 3) to achieve maximum sprint velocity (9.6 m·s⁻¹).
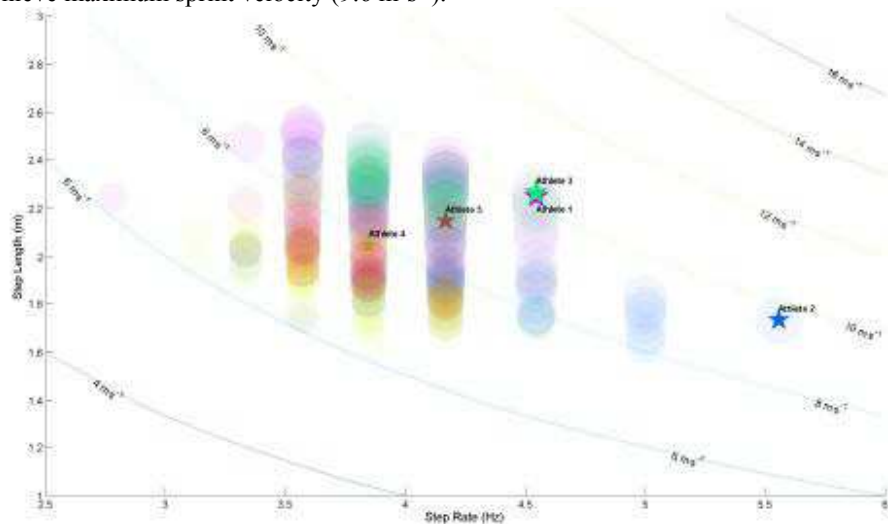


Figure 3. Relationship between step rate, step length and sprint velocity (indicated by circle size and contour lines): circle colour corresponds to each athlete with best performances highlighted by a star.

## 4. Discussion

No commercial tool – which performs fast and non-invasive analyses of sprint running gait – is currently available. The Gait Analyser automatically quantified spatio-temporal gait parameters of sprint running *in situ* (outdoors) without intrusion to athletic performance. The use of a generic system setup (sub-section 3.1) correctly identified foot contacts in 93% of trials: in 7% of trials, 12 foot contacts were incorrectly identified and 5 foot contacts incorrectly rejected (Table 1). Incorrect identification related only to Athlete 2; investigation of these trials highlighted that image segmentation was problematic for the non-uniformly coloured shoes worn by Athlete 2 (e.g. Figure 1). The cyan upper-section and magenta lower-section of the shoes yield inter-frame image differences lower than that of uniformly coloured shoes. This was exacerbated by different lighting conditions (i.e. intense sunlight or overcast) and the small physical size of the shoes worn by Athlete 2 (UK 5). Systematically higher and lower segmentation thresholds (± 23% about the generic system threshold) resolved image segmentation and foot contact identification for intense sunlight and overcast conditions respectively for Athlete 2 (i.e. sub-section 3.2). It should be noted that the generic system threshold identified 100% of foot contacts in the same conditions for Athletes 1, 3, 4 and 5.

Using optimised system setups (i.e. higher and lower image segmentation thresholds), the Gait Analyser identified 100% of foot contacts: 95% LOA for $X$ and $Y$ direction foot contacts were $44.8 \pm 232.9$ and $44.4 \pm 119.7$ mm respectively. $X$ direction errors exhibited heteroscedasticity (Table 3). This was the result of image segmentation for Athlete 2. Foot contact identification in the $X$ direction for Athlete 2 was not consistent and reflects the lowest image resolution for position data reconstructed in this direction (e.g. Figure 1). Indeed, the removal of Athlete 2's foot contact data yields homoscedastic position differences in the $X$ direction ($|r^2| = 0.00$). However, for all foot contact data, RMSE for foot contact position in the $R$ direction was 108.9 mm (Table 3). This is comparable to a previous assessment of a gait analysis system (underlying method for Gait Analyser), whereby RMSE in the $R$ direction was 103.4 mm for shod running in a laboratory [5]. Foot contact time was identified after the perceived instant of mid-stance; a weak correlation between differences indicates heteroscedasticity (Table 3). However, foot contact time RMSE was small (Table 3). For step length and step time – parameters reported to athletes – 95% LOA were $-4.9 \pm 177.7$ mm and $0.00 \pm 0.03$ s respectively. Thus error intervals represent 8.6% of the mean step length (2.06 m) and 11.7% of the mean step time (0.30 s). Step length and step time differences were homoscedastic (i.e. $|r^2| < 0.10$), indicating that these parameters were not related to measurement magnitude. Step velocity differences exhibited a weak correlation (i.e. heteroscedasticity; Table 3). However, step velocity RMSE was small (Table 3).

Sprint velocity is an important metric for athletic training and can be derived from step length and step time data. An analysis of step strategy (Figure 3) in relation to sprint velocity highlights the potential benefits and uses for the Gait Analyser. The negative relationship between step length and step rate reflects the "negative interaction" between these parameters; an increase in one factor results in a decrease in the other [2]. Comparing step length and step rate can be useful when exploring athletic step strategy. For example, Athletes 1 and 3 used similar step strategies (Figure 3) to achieve similar maximum sprint velocities (10.2 and 10.3 m·s$^{-1}$ respectively). However, the step strategy used by Athlete 2 to achieve their maximum sprint velocity (9.6 m·s$^{-1}$) was markedly different to their other performances and indeed other athletes. It is beyond the scope of this study to identify why a relatively high step rate yielded maximum sprint velocity for Athlete 2. However, the Gait Analyser was able to measure sprint step strategy *in situ* (outdoors) and non-invasively. Further, numeric results ($A_{T1}$) were reported in $1.6 \pm 1.0$ s and a video visualisation ($A_{T2}$) outputted in $1.9 \pm 1.0$ s after sprint performance.

Agreement between step length and step time estimates, combined with very short analysis times, highlight the Gait Analyser as a flexible analysis tool for non-invasive, spatio-temporal gait analysis in sprint running. Future development of the Gait Analyser should incorporate optimised segmentation thresholds identified in this study (required for 7% of trials). Image sequences could be processed using multiple segmentation thresholds simultaneously (i.e. parallel processing); the reliability of the Gait Analyser should subsequently be assessed.

## 5. Conclusion

Using standard colour images, the Gait Analyser measured spatio-temporal gait parameters of sprint running without applying markers or sensors to athletes or the running track. Analyses were performed *in situ* (outdoors) with results available in 2-3 seconds after performance. The Gait Analyser is a flexible gait analysis tool which could be applied to other scenarios that require fast, non-invasive and *in situ* gait analysis.

## References

[1] Gavrila, D.M., 1999. The visual analysis of human movement: a survey. Computer Vision and Image Understanding, 73, 82 – 98.

[2] Hunter, J. P., Marshall, R. N., McNair, P.J., 2004. Interaction of step length and step rate during sprint running. Medicine & Science in Sports & Exercise, 36, 261 – 271.

[3] Bouchrika, I., Nixon, M.S., 2006. Markerless feature extraction for gait analysis. In IEEE SMC Conference on Advances in Cybernetic Systems, pp. 55 – 61.

[4] Jung, S-U., Nixon, M.S., 2013. Heel strike detection based on human walking movement for surveillance analysis. Pattern Recognition Letters, 34, 895 – 902.

[5] Dunn, M., Haake, S., Wheat, J. and Goodwill, S., 2014. Validation of a single camera, spatio-temporal gait analysis system. Procedia Engineering, 72, 243 – 248.

[6] Dunn, M., Wheat, J., Miller, S., Haake. S. and Goodwill, S., 2012. Reconstructing 2D planar coordinates using linear and non-linear techniques. In Proceedings of the 30th International Conference on Biomechanics in Sports, pp. 381 – 383.