A proposed computer vision model for running gait assessment

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Abstract— **Running gait assessment is critical in performance optimization and injury prevention. Traditional approaches to running gait assessment are inhibited by unnatural running environments (e.g., indoor lab), varied assessor (i.e., subjective experience) and high costs with traditional reference standard equipment. Thus, development of valid, reproduceable and low-cost approaches are key. Use of wearables such as inertial measurement units have shown promise but despite their flexible use in any environment and reduced cost, they often retain complexities such as connectivity to mobile platforms and stringent attachment protocols. Here, we propose a non-wearable camera-based approach to running gait assessment, focusing on identification of initial contact events within a runner's stride. We investigated different artificial intelligence and object tracking approaches to determine the optimal methodology. A cohort of 40 healthy runners were video recorded (240FPS, multi-angle) during 2-minute running bouts on a treadmill. Validation of the proposed approach is obtained from comparison to manually labelled videos. The computing vision approach can accurately identify initial contact events ($ICC_{(2,1)} = 0.902$).**

I. Introduction

Recreational running has increased in popularity, providing a low-cost, accessible sport with significant health benefits [1]. Naturally, injury rates have increased in conjunction with the growth of the sport [2], often occurring in runners exhibiting over pronation of the foot [3]. Running shoe recommendation is a common approach to minimizing injury risk, providing various cushioning support to different running styles. However, selecting the correct running shoe requires examination of the feet to determine foot strike location and pronation during running [4].

Traditionally, running gait assessments are carried out within controlled environments, where a trained assessor will visually assess a runner's gait during treadmill running or via short over-ground runs. Critically, running gait assessment relies upon identification of initial contact (IC) points with the ground, providing insight of how the foot strikes during running [5]. However, observational, visual approaches alone lack reproducibility, validity and inter-rater reliability to quantify such a short temporal outcome [6, 7].

Consequently, use of inertial measurement units (IMU) have seen utility due to their ability to capture reproduceable, intricate gait movements at high frequency in low-resource (community-based) settings [4]. However, despite IMUs utility in running gait assessment, such approaches are bottlenecked in real-world deployment, often requiring expert intervention to attach (anatomical location must be precise, with correct device orientation) [8]. Additionally, there may be reliance on third party mobile technology for implementation with a strenuous data extraction, analysis and reporting process [9]. Equally, connectivity issues between the IMU and mobile may result in data loss.

Accordingly, research into other accessible gait assessment techniques for use in low-resource settings have become a point of interest. One approach is computer vision (CV) which has proven useful in providing low-cost, markerless human motion and gait analysis [10]. Furthermore, CV may provide more routine/pragmatic analysis of running through use of lightweight (i.e., not computationally intensive) artificial intelligence (AI) models for scalable and direct use (via embedded application/app) on smartphones [11, 12].

Here, we propose a lightweight, markerless, CV-based identification of IC events in running. This study investigates utility of AI-based approaches as well as object/foot tracking techniques for an optimal approach. By implementing a lightweight CV-based AI model, this work proposes a low-cost, scalable method of running gait assessment from a smartphone application for use in low-resource settings, negating use of additional hardware such as wearables.

II. Related work

A. Smartphone-enabled gait assessment

Smartphones have become useful to provide a platform for remote healthcare assessment in any environment, given their dramatic uptake in usage across multiple demographics [13]. Crucially, smartphones provide an accessible, highly scalable and powerful platform for digital health assessments.

Specifically, there is interest in AI smartphone applications for gait assessment [4, 14] due to their ability to autonomously provide meaningful metrics in habitual settings. However, there is often a reliance on the internet of things (IoT) which may limit their utility in low-resource settings where internet or mobile connectivity access may not be available or reliable. That warrants research into pragmatic edge computing i.e., on-device, computationally lightweight AI approaches [15].

B. Computer vision (CV) on smartphones for gait

CV is augmenting remote healthcare in a variety of applications, providing understanding of gait affecting

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pathologies, rehabilitation and sports-related domains [16]. CV-based markerless gait assessment systems are a key focus [17, 18], providing a more non-burdensome approach to gait assessment and showing use for e.g., lower limb joint angle measurement [19]. CV also removes the need for costly and time consuming researcher intervention and setup associated with wearables or applying markers to anatomical locations [20]. However, CV approaches may often utilize part affinity fields to provide key anatomical point locations, which, despite outstanding performance, require significant computational power. Such methods may be beyond the limitations of a smartphone and so limits real world use in low-resource settings. Therefore, it is pivotal that lightweight models are developed for effective use on a range of smartphones.

C. Initial contact (IC) in gait assessment

IC is the moment the foot first makes contact with the ground during gait [5]. Identifying IC informs a wide variety of assessments, such as gait cycle segmentation, understanding impact forces and gait asymmetry [21]. Within running gait assessment, examining IC is important when investigating injury rates due to excessive load and impact distribution [22]. Equally, IC enables analysis of foot strike and pronation; important features to prevent running injury, rehabilitation and optimization [4, 22].

III. METHODS

The proposed system uses lightweight CV to identify and track the feet within a video frame captured by a smartphone camera, developed in Python's OpenCV library. The tracked location of the foot informs a zero-crossing gradient analysis approach to identifying IC within running gait, *Figure 1*.

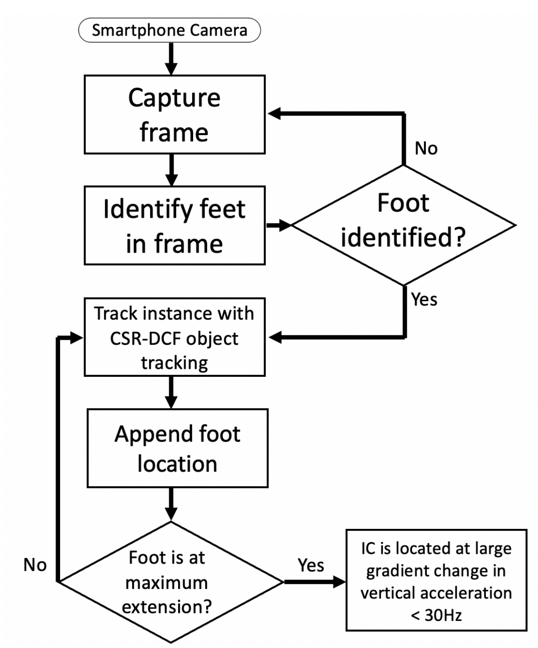

Figure 1: Flowchart of the proposed model throughput

A. Data capture and labelling

Forty healthy adult and adolescent runners were recruited from local running clubs and leisure centers in the North East of England. Ethical approval was granted by Northumbria University Research Ethics Committee (Ref: 21603). All participants gave verbal consent before testing.

Participant's lower extremities were recorded during 2-minute bouts of treadmill running at three angles (front/side/back), at a frame rate of 240 frame/second (FPS) from three iPhone X cameras, providing a high-resolution, but affordable capture of the runner's gait. Each video was captured with varying lighting and background conditions to ensure data heterogeneity. Front and back foot angles were used within training sets to provide a generalization of the foot but were emitted from testing sets for IC extraction.

Upon conclusion of data capture, videos were manually labelled such that:

1. A bounding box was drawn containing both feet for each frame, *Figure 2A*.
2. IC is labelled for relevant frames (*Figure 2B*), where IC is collected as the frame number of the video (e.g., IC located at frame 121). This process was repeated for left and right foot strike within videos.

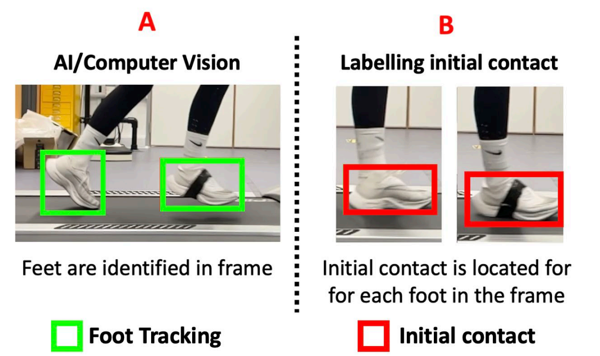

Figure 2: Labelling visualization, showing bounding box locations as the feet move (A), and time/frame of IC events (B)

B. Foot detection model part #1: Object detection

From video annotations, various object detection models were investigated and developed to automate an optimal foot tracking approach. A common 75:25 train/test split ratio of video image labels was adopted for retraining three gold/reference standard object detection models (*faster RCNN inception v2, rfcn resnet101, ssd mobilenet_v2*) with transfer learning, trained utilizing a deep learning server (12GB Nvidia K80, 16GB RAM, Python 3.8, TensorFlow 1.15.2). During training, a grid search optimization strategy was deployed to ensure maximum performance and efficiency through autonomous benchmarking [23].

C. Foot detection model part #2: Foot tracking

Upon first detection of a foot from the object detection component, an object tracking instance was implemented to track the foot in the video. The vector location (X, Y) of each tracked foot is stored for every video frame for further analysis, *Figure 3*. A combination of high performing object tracking approaches [24] within Python's OpenCV library were investigated. These included *discriminative correlation filter with channel and spatial reliability* (*CSR-DCF*) and *kernelized correlation filter* (*KCF*), to determine the optimal combination of foot detection/tracking method.

D. *Foot detection model part #3: Gradient analysis*

IC is the point of first impact with the ground after a full stride extension [5]. As such, a maximum extension of the leg is identified through locating a zero-crossing gradient peak within the horizontal foot plane. Once identified, a 30-frame region of interest (equating to 0.125s) is searched for the largest gradient change in vertical location (i.e., foot has stopped accelerating in the vertical plane), denoting an IC event *Figure 3, Algorithm 1*.

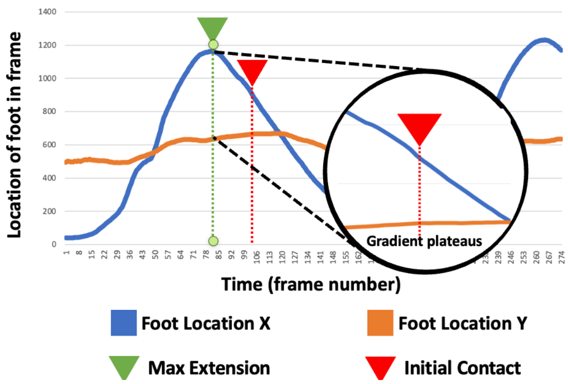

Figure 3: Vector location of foot X/Y extracted from foot tracking system with max extension and initial contact (IC)

Algorithm 1 Initial contact (IC) identification

Require: Vector location (X,Y) of foot in video stream data

Ensure: Identify initial contact

```
for frame in video_stream:
    if horizontal frame foot location is a gradient crossing peak:
        append max_extensions list
for max_extension in max_extensions
    ROI = max_extention + 30 frames
    IC = MAX gradient change in vertical movement
```

return frame number where IC exists within each video stream

A. *Statistical analysis and benchmarking*

A standardized Intersection-over-Union (IoU) benchmark was used to evaluate the performance of the object detection and tracking models, providing a percentage of 'overlap' (i.e., how close are the labelled and predicted bounding boxes) [25]. To evaluate correlation between IC identification algorithm and manually labelled videos, Pearson's and intra-class correlations ($ICC_{(2,1)}$) were used. ICC Performance was evaluated in line with previous thresholds [26] i.e., poor (< 0.5), moderate (0.5-0.75), good (0.75-0.9) or excellent (> 0.9).

IV. Results

No data loss was reported across the cohort of participants. 25% of the cohort were utilized for benchmarking the model, (4328 manually labelled frames, 92 points of IC). Results of the models are presented as, (*A*) classifier accuracy, followed by (*B*) IC estimation benchmarks.

A. *Foot detection and tracking*

A grid-search optimization approach of model backend and object tracking was utilized to autonomously search the best configuration within Python's OpenCV object tracking module and TensorFlow's re-trainable models, *Table 1*. Observing the IoU of each model, an optimal rating of 0.913 across all labelled images in the test dataset demonstrated the highest performance for *faster_rcnn_inception_v2* with *CSR-DCF* object tracking.

Table 1: Top performing model results with different backends and object tracking. Data shortened for brevity. FPS (frames per second) shown to evaluate execution time optimization.

AI model	Object tracking method	IoU	FPS	*p*	$ICC_{(2,1)}$
faster rcnn inception v2	***CSR-DCF***	**0.913**	**22**	**0.891**	**0.902**
faster rcnn inception v2	*KCF*	0.874	24	0.894	0.890
rfcn resnet101	*CSR-DCF*	0.799	18	0.752	0.776
rfcn resnet101	*KCF*	0.833	18	0.821	0.844
ssd mobilenet v2	*CSR-DCF*	0.831	27	0.809	0.810
ssd mobilenet v2	*KCF*	0.774	28	0.761	0.730

B. *IC Idenification*

Results were moderate to good for all AI approaches (>0.730). However, excellent $ICC_{(2,1)}$ (0.902) and Pearson's (0.891) were evident between manual labels and the best combination of *faster_rcnn_inception_v2* and *CSR-DCF* object tracking approach to inform a gradient analysis IC extraction layer, *Table 1*.

V. Discussion

The proposed model/method aims to identify IC from a 2D-video stream in running gait through utilization of object detection, tracking and gradient analysis. This work provides the foundation towards a novel, low resource, lightweight, accessible running gait analysis tool, with potential application on a smartphone in low-resource settings. The methodology suggested here, identification of IC from a 2D-video stream, works towards satisfying the need for a low-cost gait assessment [6] by removing the reliance upon wearable technology and/or manual intervention.

The presented methodology performs comparably to approaches utilizing both wearable technology and computationally complex models such as *OpenPose* based human activity recognition, providing groundwork for the segmentation of gait in habitual environments [19, 27, 28].

A. *Limitations*

Video capture was performed in community-based, low-resource environments. This resulted in real world video quality such as varying brightness levels and capture qualities. However, we estimate occlusion (i.e., when a foot obscures another) during video capture sessions to be the primary factor negatively impacting accuracy. Occasionally (3 in 40 video streams), feet may leave the frame, thus becoming completely occluded. In this occurrence, the vector location of the foot is naively assumed to be stationary. Location capture is resumed when the foot is re-identified, in line with the function of CSR-DSF object tracking [24].

A. Future work

The presented work focuses on identification of IC in running gait, providing a baseline towards augmenting a full running gait assessment. Future work will involve validation and extraction of useful running gait outcomes such as pronation foot strike, and ground contact time. Those will help inform injury prevention and running economy metrics. Furthermore, the utility of a low resource, non-invasive gait assessment tool could be applied to different gait analysis applications, with existing work addressing the assessment of older adult health and gait affecting pathologies [29]. As such, the validity of the approach in identifying IC in different gait cohorts is required to move towards a scalable, non-invasive, clinically relevant gait assessment tool.

Our approach opted to use CSR-DCF object tracking as a result of a grid-search demonstrating high performance with low execution times, *Table 1*. Currently, new developments in deep learning-based, occlusion aware object tracking systems have shown excellent performance in complex scenes [30]. With developments of model-minimization libraries such as *TFLite* and dedicated deep-learning processors becoming ubiquitous in modern machines [31], accuracy could be further optimized in future iterations. Extending the utility of *TFLite,* proceeding work will benchmark the model's performance from a smartphone application when compiled down to an embedded model, providing a ground for a smartphone-based remote gait assessment.

VI. Conclusion

The proposed running gait assessment approach uses CV and gradient analysis to identify IC from a 2D video stream captured from a smartphone. Considering ICs importance for robust gait assessment, provision of a valid, scalable and pragmatic approach for use in low resource running gait analysis is essential. Here, the proposed model may help to remove barriers to running gait assessment, providing useful data to inform injury prevention and rehabilitation.

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