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# A real-time feedback method to reduce loading rate during running: Effect of combining direct and indirect feedback

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**ABSTRACT**

Impact loading plays a key role in the pathophysiology of running-related injuries. Providing real-time feedback may be an effective strategy to reduce impact loading; however, it is currently unclear what an effective training method to help runners achieve a habitual low loading rate is. We subjected 20 healthy non-runners to a structured sequence of direct and indirect biofeedback designed to facilitate broader exploration of neuro-mechanical workspace for potential movement solutions (indirect feedback on cadence and foot-strike angle) and to refine and converge upon an optimal sub-set of that space to match the task goal (direct feedback on loading rate). While indirect biofeedback on foot-strike angle yielded a lower impact load than providing direct biofeedback on loading rate, compared to indirect biofeedback on foot-strike angle, providing direct feedback on loading rate statistically increased (+58%, p = 0.007) the range of goal-relevant solutions participants used to lower their impact loading. Results showed that structured feedback was effective in increasing the range of input parameters that match the task goal, hence expanding the size of goal-relevant solutions, which may benefit running performance under changing environmental constraints.

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**KEYWORDS**
Loading rate; motor control; foot strike; cadence; adaptation

## Introduction

Compiling evidence indicates that ground-to-limb impact loading plays a key role in the pathophysiology of running-related injuries (Bredeweg et al., 2013; Pohl et al., 2009; Zadpoor & Nikooyan, 2011; Zifchock et al., 2008). This impact load, caused by the decelerating limb rapidly changing its momentum at initial contact, reaches up to three times the weight (Nigg, 1997) and generates a transient force that is transmitted along the musculoskeletal system. Many retrospective studies (Milner et al., 2006; Pohl et al., 2009; Zadpoor & Nikooyan, 2011; Zifchock et al., 2008) have shown a correlation between repetitive high loading rates experienced while running and lower extremity overuse injuries. For instance (Zifchock et al., 2008) showed that the injured leg displayed higher loading than the non-injured leg during running. In a recent prospective study, Davis, et al. (Davis et al., 2015) reported that high loading rates distinguish between runners that would not get injured and those that would acquire a positive diagnosis of a running-related injury. These examples underpin a widely accepted theory, that minimizing impact load will help reduce a runner's risk of injury. However, determining an effective training method to help runners achieve a habitual low loading rate requires more research.

Control of impact load is a challenge for runners due to its transient nature, however, receiving real-time biofeedback of associated biomechanical measurements can enable self-regulation of this task-goal. This biofeedback information can express the quantity of a parameter that has either a direct, or an indirect, association with the task goal. As an example of goal-indirect feedback, research has shown that parameters such as cadence (Clarke et al., 1985; Heiderscheit et al., 2011; Samaan et al., 2014) and foot-strike angle (Cheung & Davis, 2011; Giandolini et al., 2013; Shih et al., 2013) cause an effect on loading rate. The biomechanical explanation is that a high cadence will typically reduce the flight trajectory of the body centre-of-mass and cause load reduction, while an increased inclination of the foot angle at impact will reduce limb stiffness and likewise cause load reduction. Here, we use a mathematical model to provide the metalanguage that clarifies this cause–effect relationship within the locomotor control system (Karnaukhov, 2006). For example, cadence and foot-strike angle are the input parameters of some function [i.e., $F(\text{input}) + \varepsilon = \text{output}$], while the output is the loading rate, and "$\varepsilon$" is a random error due to the inherent nature of an open nondeterministic locomotor system. In accordance with the concept of motor equifinality, multiple motor inputs can form a goal-relevant set of solutions with a target output (Cusumano & Cesari, 2006). Hence, the locomotor control system can receive direct feedback of the output (effect) and attempt to learn the inputs (causes), or alternatively, receive indirect feedback of selected inputs (causes) and attempt to learn how they influence the output. Because limitations are inherent to both feedback approaches, it may be an insufficient method to prescribe only one form of

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feedback. Therefore, when the locomotor control system attempts to learn an effective map between cadence and foot-strike angle (input) on loading rate (output), it should benefit from a two-way approach, where it finds forward solutions by employing an indirect mapping process, and it finds an inverse solution by employing a direct mapping process. For a runner, the benefits of an indirect feedback approach can offer tangible access to technique-related information by self-regulating movement patterns using a target goal (i.e., control of the input parameters); thereby, the runner explores and experiences a broad range of initial conditions without knowing the effect. In contrast, the benefit of direct biofeedback is that it requires a more active process to self-discover the optimal set of initial conditions that cause the reduction in loading rate (output) (Lauber et al., 2013; Maia Pacheco et al., 2019; Mulloy et al., 2019). When feedback structure is designed to facilitate broader exploration of neuro-mechanical workspace for potential movement solutions (indirect feedback); then, there appears to be greater success when attempting to refine and converge upon an optimal sub-set of that space to match the task goal (direct feedback) (Richards et al., 2018). This feedback approach is claimed to increase the range of input parameters that match the task goal, hence expanding the size of goal-relevant solutions (Wu & Latash, 2014). Recently, Baggaley, et al. (Baggaley et al., 2017) investigated the effect of direct and indirect biofeedback on the loading rate. They adopted a randomized feedback approach and concluded that indirect feedback of foot-strike angle was more effective at reducing average loading rate than either cadence or average loading rate. These results indicate that foot-strike angle is a more critical input parameter than cadence when the system solves the forward problem (i.e., indirect control overloading rate is achieved by controlling the input). Furthermore, the locomotor system was comparably less effective at solving the inverse problem of direct control over loading rate (output). However, for the case of loading rate training, it is unknown whether preliminary indirect feedback conditions will enhance the effect of direct feedback.

Therefore, the aim of this study was to structure the sequence of indirect and direct biofeedback to assess the merits of direct feedback. We used the same biofeedback parameters as (Baggaley et al., 2017), but we sequenced the order of biofeedback: (i) loading rate 1 (direct), (ii) step cadence (indirect), (iii) foot-strike angle (indirect), and (iv) loading rate 2 (direct). We quantified the set of goal-relevant solutions by projecting a set of bi-varying points in tri-variate space (i.e., loading rate, cadence and foot-strike angle) onto a manifold space that represents the task goal (Müller & Sternad, 2004). Since, by definition, every point in the task manifold corresponds to biomechanical state that optimizes loading rate, the area of the projected points will give us a metric to express the size of goal-relevant solutions. Based on previous results (Baggaley et al., 2017) our first hypothesis is that providing indirect biofeedback on foot-strike angle will be more effective compared to direct biofeedback of loading rate. The second hypothesis is that the second direct biofeedback will result in a larger area of goal-relevant solutions of foot strike and cadence compared to indirect biofeedback of foot-strike angle. The third hypothesis is that the first direct biofeedback will be less effective at solving the inverse problem compared to the second direct feedback.

## Methods

### *Participants*

Twenty healthy male participants (age 28.1 ± 2.8 years, height 176 ± 1.3 cm weight 75.8 ± 5.7 kg) were recruited from a population of active people not participating in construct running training, but had experience with treadmill running. No participant was previously exposed to real-time biofeedback protocols or had been involved in studies requiring adjustment of running form. A priori power calculation (GPower) based on Baggaley et al. 2017 ($d$ = 0.87; $f$ = 0.435), alpha = 0.05, power 80% gave a total sample size of 18 participants, and 2 extra participants (10% of required sample size) were recruited to account for attrition. Participants were fully informed of the risks involved in participating in the experiment and they provided written consent to participate. Study received ethical approval by the research team's University Ethics Committee (ref 24315).

### *Experimental protocol*

Forty-one reflective markers were used to track the position and orientation of the trunk (3 markers), pelvis (4 markers), thighs (5 markers each), shanks (5 markers each), and feet (7markers each). Digitized landmarks were created to define the knee and ankle position, with functional movements defining the axis of rotation of the knee and the hip joint centre (Besier et al., 2003) (for details of the model see Appendix A). All participants wore the same shoe model (Merrell®, Rockford, Michigan, USA), defined as "neutral" by the Minimalist index scale (Esculier et al., 2015). After model calibration, participants underwent a warm-up on an instrumented treadmill (DBCEEWI, AMTI, USA) with incremental speed: starting from 6 km/h (1.66 m/s) for two minutes, speed was then increased to 8 km/h (2.22 m/s) for two minutes, 9 km/h (2.5 m/s) for two minutes, and 11 km/h (3.05 m/s – testing speed) for the last three minutes of the warm-up. This running speed was chosen as it has been found in a pilot study to be biomechanically comfortable enough to allow maximal focus on the real-time biofeedback.

After a four-minute break, participants began with the testing protocol, which comprised 5 four-minute running trials at 11 km/h interspersed with four-minute breaks. Participants started with the baseline condition (BSL) during which they were not required to follow any biofeedback. After BSL, participants performed the four experimental conditions in the following order: loading rate (LOAD1), two biofeedback conditions on the secondary variables – cadence (CAD) and foot-strike angle (FSA) – presented in a (selected at priori) randomly order, and a second loading rate (LOAD2). In each condition, cadence (in step/min), foot-strike angle (in degrees), and loading rate (in BW/s) were recorded over the 4 minutes of running.

Real-time biofeedback was presented on a 50″ TV screen placed 2 m in front of the treadmill at eye level. During CAD a vertical bar graph represented the cadence signal streamed in real-time with a range fixed between +10% and +15% from the mean cadence recorded at BSL, this range was chosen based on past findings that such increase in cadence substantially reduces tibial acceleration (Derrick et al., 1998; Hamill et al., 1995; Heiderscheit et al., 2011; Hobara et al., 2012). Participants were instructed to "keep the vertical bar within the range". During FSA the biofeedback was a continuous signal representing the angle between the treadmill floor and the foot segment (both left and right) on the sagittal plane (dorsi-plantarflexion), and a range was fixed between 0 and −10 degrees of dorsiflexion, consistent with a previously published procedure (Baggaley et al., 2017). Participants were instructed to "keep the peaks within the range". During LOAD1 and LOAD2, a vertical bar graph was displayed representing the computed loading rate for each step. Participants were instructed to "keep the vertical bar as low as possible". CAD, FSA and LOAD2 conditions were preceded by a one-minute reference condition (REF) during which participants were asked to run without any biofeedback. REF trials were designed to ensure running patterns reversed back to baseline before commencing a new experimental trial. At the end of each trial, the rate of perceived exertion scale (RPE) was administered to participants. Overall, the protocol had 30 minutes of running (warm-up included).

## Data processing

While cadence and foot-strike angle were directly computed and displayed in real-time through the Visual3D Real-time tab (C-Motion, Inc., Rockville, MD, USA), for the loading signal, we accessed the vertical component (Fz) of the analogue output of the force plate amplifier (AMTI Gen5). This output was fed into an analogue input of a microcontroller (PIC). Two analogue thresholds were programmed into the firmware of the PIC, in this case, corresponding to 20% and 100% of body weight (BW). These are common thresholds used to compute average loading rate (Milner et al., 2006). The 16-bit timer in the PIC was then used to measure the time taken for the force to rise from 20% to 100% BW. The time resolution of the complete process was 240 μs (4 kHz). Immediately after the timer has been read, floating point mathematics in the PIC computed a digital value for the loading rate dividing the fixed normalized force value (80% BW) by the change in time. This value was sent to a digital-to-analogue converter for generating the analogue output that was fed back into the motion capture system (Nexus, Vicon Motion Systems, UK). Analogue signal was then streamed through the V3DServer (C-Motion, Inc., Rockville, MD, USA) into the V3D Real-time tab (C-Motion, Inc., Rockville, MD, USA) for displaying (Figure 1). Post-processing, all signals were exported in Visual3D$^{TM}$ software (C-Motion, Inc., Rockville, MD, USA) in order to compute mean cadence, mean foot-strike angle, and mean loading rate for each trial: BSL, CAD, FSA, LOAD1-2, and REF1-3. Kinematic and kinetic data were filtered at 15 Hz and 35 Hz, respectively, while no filter was applied to the loading rate signal. Foot-strike angle was the angle between foot and treadmill deck at foot contact event. This event was identified as the first instance the vertical component of the ground reaction force passed a minimum threshold of 20 N. Cadence was defined on a step-by-step basis using the formula CAD = 60/step time; while the loading rate value at each step was obtained by reading the loading rate signal at a time between two consecutive foot contact events.

## Data analysis

For each participant, the mean and standard deviation for loading rate, cadence, and foot-strike angle metrics were obtained from a set of 350 strides, from each test condition. Step-by-step time series data for cadence and foot-strike angle were exported to Matlab (The Matworks®, Inc., Natick, Massachusetts, United States), where data from each participant were concatenated in one vector per variable. Each value within the vector was transformed by its magnitude from the minimum value and relative to the data range, forming a rescaled vector set [0 1], using the formula:

$$X_r = \frac{Xi - \min(X)}{\max(X) - \min(X)} \tag{1}$$

where $Xi$ is the $i$ value of the time series $X$, and $X_r$ is the rescaled value $i$. Data was then separated back into independent conditions. This procedure ensured normalization of the data and it simplified comparisons between individuals. The task manifold

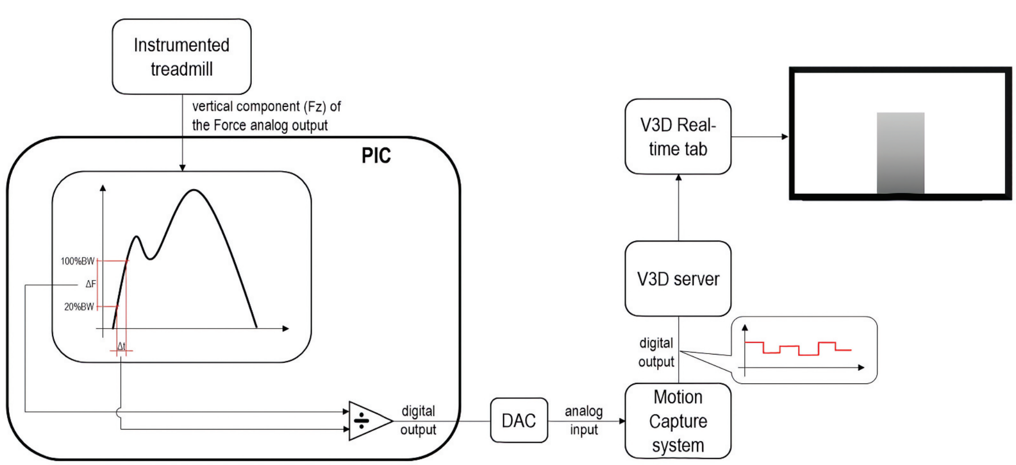


Figure 1. Schematic representation of the components and process of how direct feedback on loading rate was computed and presented.

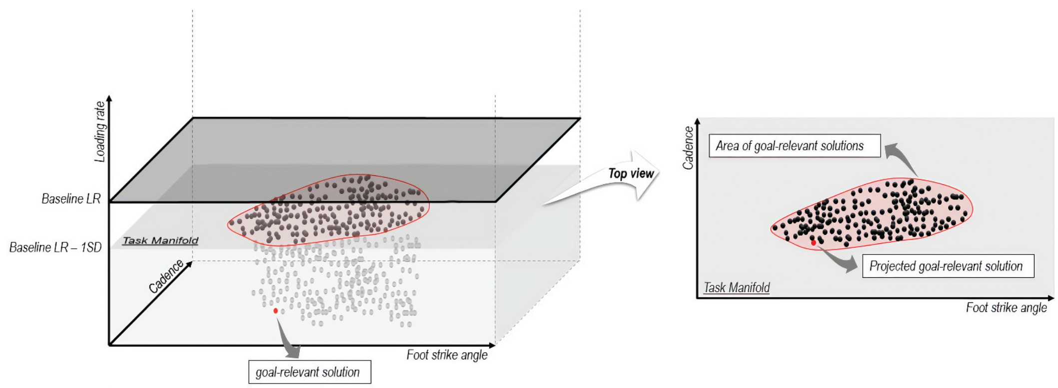


Figure 2. Illustration of how the three variables co-vary in a cloud of data points. A task manifold (2D plane) defines the surface containing all possible combinations of cadence and foot-strike angle with a corresponding loading rate lower than the mean loading rate value for the baseline condition minus one standard deviation. The fitted ellipse area of projected points on the manifold defines the size of goal-relevant solutions.

is a quasi-measure of motor equifinality (Cusumano & Dingwell, 2013), defined as a planar sub-space where co-varying cadence and foot-strike angle correspond with a loading rate lower than the mean loading rate value for the baseline condition minus one standard deviation (Figure 2). The area covered by the projected set of bi-varying points onto the manifold space was then computed for each experimental condition using the boundary function in Matlab (The Matworks®, Inc., Natick, Massachusetts, United States), with a default shrink factor of 0.5, and reported as arbitrary units (a.u.) squared.

### Statistical analysis

A repeated-measures ANOVA with condition (BSL, CAD, FSA, LOAD1, LOAD2) as fixed factor was performed on cadence, loading rate, foot-strike angle and RPE values separately. The analysis was performed on the participants' means and standard deviations of the dependent variables. Multiple comparisons with Bonferroni adjustment, and mean difference between conditions along with 95% confidence interval were calculated. Furthermore, a repeated-measures ANCOVA with condition (BSL, CAD, FSA, LOAD2) as fixed factor was computed on loading rate using the average loading rate on LOAD1 as covariate, to test whether a participant's intrinsic ability to lower the load influenced loading rate in the other conditions. Prior to conducting ANOVAs, the assumption of normality was checked through the analysis of skewness and kurtosis of the data distribution and visual inspection of boxplots. Data associated with skewness less than 2 and kurtosis less than 9 were evaluated as normally distributed (Schmider et al., 2010). Considering the within-participant analysis, the assumption of homogeneity of variance was not needed. A paired sample t-test on the area defined by the combinations of foot-strike angle and cadence able to decrease loading rate compared to baseline was performed to analyse goal-relevant solutions. We also performed a linear multiple regression to identify the contribution of foot-strike angle and cadence in explaining variance in loading, and Pearson correlation coefficient determined whether a correlation existed between loading rate and foot-strike angle. All statistical analyses were run using SPSS (version 25.0. Armonk, NY: IBM Corp.). Significance was set at $p < 0.05$ for all the analyses and the magnitude of changes was assessed using Effect Sizes ($\eta_p^2$) and defined as follows: <0.01 trivial, 0.01–0.06 small, 0.06–0.14 moderate, and >0.14 large (Cohen, 1988).

## Results

The assumption of the normal distribution of the data was met in all the analyses (skewness = 0.08 to 1.9; kurtosis = 0.24 to 5.58). Means and standard deviations of loading rate, cadence, and foot-strike angle in all five conditions are presented in Figure 3.

### Loading rate

There was a statistically significant effect of condition in loading rate ($F[4,17] = 21.28$, $p < 0.01$, $\eta_p^2 = 0.56$). The multiple comparisons analysis showed that loading rate in BSL was significantly higher than FSA ($p < 0.01$, delta = 62 [LI = 39, UI = 86]), LOAD1 ($p < 0.01$, delta = 35 [LI = 7, UI = 63]) and LOAD2 ($p < 0.01$, delta = 54 [LI = 28, UI = 80]); loading rate in FSA was significantly lower than CAD ($p = 0.01$, delta = −37 [LI = −67, UI = −7]) and LOAD1 ($p < 0.01$, delta = −27 [LI = −47, UI = −8]). Furthermore, while not being statistically significant, a close inspection of confidence interval suggests that loading rate in CAD was meaningfully lower than BSL ($p = 0.057$, delta = −25 [LI = −51, UI = 0.5]), LOAD2 was meaningfully lower than CAD ($p = 0.056$, delta = −29 [LI = −58, UI = 0.5]) and LOAD1 ($p = 0.053$, delta = −19 [LI = −38, UI = 0.1]). There was no statistically significant difference between FSA and LOAD2 conditions.

ANCOVA showed a significant effect of condition ($F[3, 17] = 7.46$, $p < 0.01$, $\eta_p^2 = 0.32$). Multiple comparisons analysis showed that loading rate in BSL was higher than CAD ($p < 0.01$, delta = 25 [LI = 6, UI = 45]), FSA ($p < 0.01$, delta = 62 [LI = 40, UI = 84]), and LOAD2 ($p < 0.01$, delta = 54 [LI = 30, UI = 79]); loading rate in CAD was significantly higher than FSA ($p < 0.01$, delta = 37 [LI = 14, UI = 60]) and LOAD2 ($p < 0.01$, delta = 29

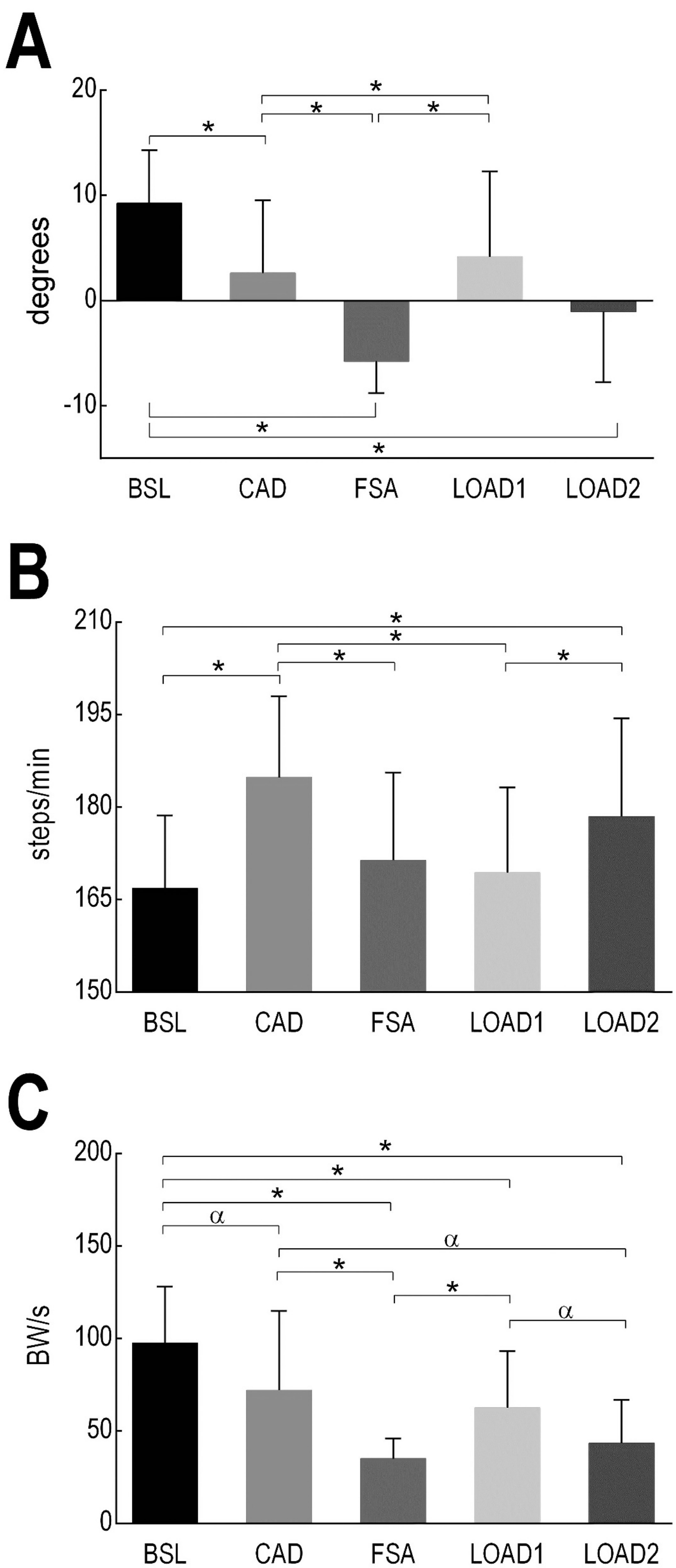


**Figure 3.** Mean and SD for foot strike (A), cadence (B), and loading rate (C) among baseline (BSL) and all experimental conditions in which participants were asked to control a specific variable: cadence (CAD), foot-strike angle (FSA), loading rate pre (LOAD1), and loading rate post (LOAD2). * indicates statistically significant differences ($p < 0.05$). α indicates meaningful differences.

[LI = 3, UI = 54]); no statistical difference between FSA and LOAD2.

The result from multiple regression shows that foot-strike angle and cadence statistically significantly predict loading rate, $F(2,87) = 54.5$, $p < 0.01$, $R^2 = .556$. Only foot-strike angle added statistically significantly to the prediction, $p < 0.01$ (Appendix B).

### Cadence

There was a statistically significant effect of condition in cadence ($F[4,17] = 26.3$, $p < 0.01$, $\eta_p^2 = 0.61$). The multiple comparisons analysis showed that cadence in CAD was significantly higher than BSL ($p < 0.01$, delta = 18 [LI = 15, UI = 21]), FSA ($p < 0.01$, delta = 13 [LI = 6, UI = 20]), and LOAD1 ($p < 0.01$, delta = 15 [LI = 11, UI = 20]); cadence in LOAD2 was significantly higher than BSL ($p < 0.01$, delta = 12 [LI = 3, UI = 20]) and LOAD1 ($p < 0.01$, delta = 9 [LI = 3, UI = 16]); there was no significant difference in cadence between CAD and LOAD2, LOAD2 and FSA, FSA and BSL, and LOAD1 and BSL.

### Foot-strike angle

There was a statistically significant effect of condition in foot-strike angle ($F[4,17] = 25.8$, $p < 0.01$, $\eta_p^2 = 0.60$). The multiple comparisons analysis showed that foot-strike angle in BSL was significantly higher than CAD ($p < 0.01$, delta = 7 [LI = 2, UI = 11]), FSA ($p < 0.01$, delta = 15 [LI = 11, UI = 19]), and LOAD2 ($p < 0.01$, delta = 10 [LI = 5, UI = 16]); foot-strike angle in FSA was significantly lower than CAD ($p < 0.01$, delta = −8 [LI = −14, UI = −3]), LOAD1 ($p < 0.01$, delta = −10 [LI = −16, UI = −4]), and LOAD2 ($p = 0.03$, delta = −5 [LI = −9, UI = −0.4]); foot-strike angle in LOAD2 did not significantly differ to CAD and LOAD1, foot-strike angle in CAD did not significantly differ to LOAD1.

There were no statistical differences ($p > 0.05$) between any of the REF conditions and baseline for either foot-strike angle, cadence, or average loading rate, ensuring that all runners reverted back to baseline state before commencing a new feedback condition.

### Goal-relevant solution

The range of goal-relevant solutions that participants were able to use during LOAD2 was statistically ($p = 0.007$) larger (+58%) than the solutions found during FSA condition (35.8 vs 18.5 a.u. (Bredeweg et al., 2013) respectively, Figure 4).

## Discussion

This study provides new evidence on how real-time visual biofeedback can be used to reduce the impact load during running. Our first hypothesis was partially confirmed, where indirect biofeedback on foot-strike angle would yield a lower impact load than providing direct biofeedback (LOAD1 or LOAD2). LOAD1 condition was not different from CAD in mean loading rate, and higher than FSA and LOAD2 conditions. Both FSA and LOAD2 conditions were effective at lowering the loading rate to less than half (−58%) of the baseline value, which was a larger reduction compared to Baggaley, et al. (2017). The decreased loading rate in the FSA condition is consistent with a decreased ankle

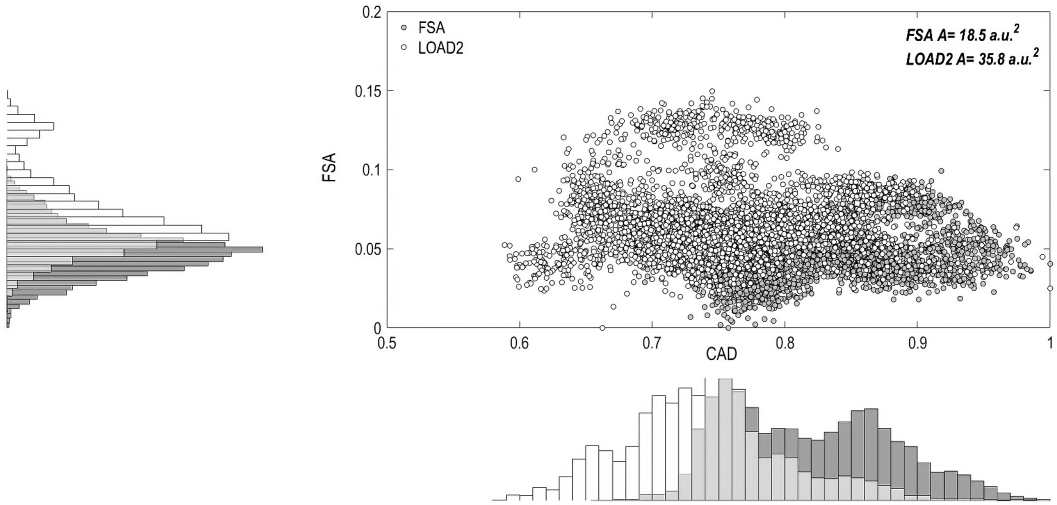


Figure 4. Distribution of functional combinations of cadence and foot strike (normalized values). Comparison is between the FSA condition (grey) and LOAD2 condition (white).

joint stiffness (Garofolini et al., 2019) and leg stiffness (Shih et al., 2019). However, although mechanically sound, using an increased plantarflexed foot strike as an isolated strategy may not be sufficient and functionally limiting. Over time this strategy may be dangerous for the body, possibly leading to injurious consequences (Wheat, 2005) such as patellofemoral pain (Kulmala et al., 2013).

The second hypothesis that the second direct biofeedback (LOAD2) will result in a larger area of goal-relevant solutions of foot strike and cadence compared to indirect biofeedback of foot-strike angle (FSA) was confirmed. Despite lowering load similarly, LOAD2 resulted in a larger area of goal-relevant solutions than FSA (+58%; Figure 4). This may promote adaptability to changing task and environmental constraints, as runners will have a larger repertoire of solutions to "choose" from, and a higher likelihood to satisfy the new task demands. While this may suggest that using direct biofeedback on loading rate is beneficial, this result is conditional to the provision of information (third hypothesis). Providing participants with information about functional movements has been shown to facilitate learning (Kernodle & Carlton, 1992; Newell et al., 1990) beyond the presentation of a feedback variable alone. In fact, instructing the runner to decrease loading rate, which can be ambiguous to non-runners and non-biomechanists, was somewhat effective the first time (LOAD1), but less effective than LOAD2. After runners had access to technique-related information like increasing cadence and changing their foot-strike pattern in CAD and FSA, when they were given the direct biofeedback again (LOAD2), they knew alternative movement strategies to modify this ambiguous metric and their performance improved. Therefore, in agreement with our third hypothesis, self-regulation in LOAD1 did not enable participants to fully explore the space of candidate solutions to match the task goal (Newell, 1991). Thus, direct biofeedback on load should be preceded by indirect biofeedback on the main strategies (Richards et al., 2018) (i.e., decrease foot strike, increase cadence); this will channel the search towards a set of co-varying states that may be a more optimal match for the task goal. Indirect biofeedback can be provided both explicitly – by verbally instructing the participant – or, as we did, implicitly by making the participant experiencing the effect of decreased foot-strike angle, and increased cadence on loading rate. Despite not testing this hypothesis, we consider the former strategy to be less effective because verbal instructions do not inform the participant on how to navigate through the space to find goal-relevant solutions (P. L. Laguna, 2008; P. Laguna, 2004). Previous research has also shown that implicit learning is more robust under changing task and environmental constraints than explicit learning (Masters et al., 2008); we therefore suggest implicit strategies to be used by practitioners.

The main limitation of the study is that we tested recreational runners. While results may be generalized to a wide group of runners, more experienced runners may already be familiar with the concept of loading rate and the functional strategies that can be used to lower it. In this and previous studies (Baggaley et al., 2017; Crowell et al., 2010; Van den Noort et al., 2015; Wood & Kipp, 2013), experiments were run indoor, on a treadmill, in standardized and controlled conditions, and the issue of adapting solutions to reduce load according to changes in task constraints was trivial. However, task and environmental conditions do change in outdoor running, and learning to reduce loading rate by following the indirect and direct method of biofeedback may be advantageous. We suggest future research addressing this issue – how to provide direct and indirect feedback outdoor – which has important practical implications for coaches and runners, using, for example, accelerometer data (Chan et al., 2020). Moreover, this was an acute intervention and we did not examine the learning effect via retention or transfer tests. This limitation was accepted, as the research question related to complex, multiple interactions. However, in future studies, it will be important to test the persistence of performance under the same conditions as the biofeedback training (retention), and persistence of performance under different conditions from training (transfer) using measurements of stability and/or adaptability (Margill, 2003) to determine the effectiveness of the biofeedback. In addition, although we argued that direct biofeedback on loading can be a valid option when it comes to "teach" or "retrain" people on reducing the impact load during running (Crowell & Davis, 2011; Crowell et al., 2010; Ericksen et al., 2015; Wood & Kipp, 2013), a randomized controlled trial is needed to confirm if this kind of biofeedback may be more beneficial, and less limiting, for training and retrain purposes than providing indirect biofeedback on secondary variables – foot-strike angle and cadence. Lastly, the basic idea of task manifold and goal-relevant solutions underpins multiple methods of covariance analysis (Latash et al., 2002; Müller & Sternad, 2004; Scholz & Schöner, 1999; Schöner & Scholz, 2007; Sternad et al., 2011). In contrast to more complex analysis (i.e., uncontrolled manifold analysis) using the same basic idea, our approach was simpler and did not (did not need to) meet some of the assumptions that are required in such complex analytical methods.

### *Perspective*

Previous work demonstrated that multiple strategies can lower the loading rate (Baggaley et al., 2017). However, it is still unclear whether it is possible to reduce the load by changing foot strike while keeping a constant cadence; hence, the effect of reduced foot strike boasted as "*the solution*" (Davis et al., 2017) may be partially explained by an increased cadence. It will be naïve to disregard cadence control as ineffective without acknowledging that a complicated relationship exists between foot-strike angle and cadence, so that it is very unlikely that someone running at constant speed is able to change foot strike without changing cadence and vice versa (unless forced to do so). Our results revealed that the interactive effect of cadence and foot-strike angle is only partially explaining variance in loading rate; thus, other gait variables such as leg stiffness (Shen & Seipel, 2018, 2015) may be responsible for loading control and ultimately the development of running-related injuries (Granata et al., 2002; Williams et al., 2003). In future studies, long-term effects of training intervention using direct biofeedback on loading should be evaluated, and the essential properties of the embodied neuro-musculoskeletal system that influence the leg force-length dynamics during loading more deeply considered.

## Conclusion

Loading rate can be effectively reduced using both direct and indirect visual biofeedback. The use of direct biofeedback on loading, as opposed to indirect biofeedback on cadence or foot-strike angle, may unable the participants to explore a larger set of goal-relevant solutions. However, this requires preconditioning (informing either implicitly or explicitly) on what kinematic strategies are functional to the task. We proposed a structured sequence of direct and indirect biofeedback to facilitate the adoption of goal-relevant solutions, which may benefit running performance under changing environmental constraints.

## Disclosure statement

No potential conflict of interest was reported by the authors.

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