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AI-Based Footwork Pattern Detection and Its Impact on Response Time: An A-B Single-Case Study

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Abstract. Footwork patterns play a critical role in athletic performance, particularly in sports requiring rapid directional changes and agility. This single-case A-B experimental design study investigated the effectiveness of artificial intelligence-based footwork pattern detection systems in improving response time among athletes. The study involved one elite athlete participant engaged in a controlled environment over 12 weeks, comprising 6 weeks of baseline (A) assessment and 6 weeks of intervention (B) with AI-supported real-time feedback. Response time was measured using photographic timing systems, while footwork patterns were analyzed through computer vision algorithms. Results indicated a mean reduction in response time of 8.7% during the intervention phase compared to baseline, with visual analysis suggesting clinically meaningful improvement in pattern consistency. The findings suggest that AI-based footwork detection systems may serve as effective tools for enhancing athletic performance and response time through real-time biomechanical feedback. However, the single-case design limits generalizability, indicating the need for larger-scale studies to corroborate these findings. This research contributes to the growing literature on artificial intelligence applications in sports science and performance optimization.

Keywords: artificial intelligence, footwork detection, response time, single-case design, athletic performance, biomechanics.

1 Introduction

Athletic performance depends on multiple physiological and biomechanical factors working in concert to produce optimal outcomes. Among these factors, footwork represents a foundational element that determines an athlete's ability to execute rapid directional changes, maintain balance during dynamic movements, and respond swiftly to environmental stimuli.(Gabbett & Whyte, 2021) The quality of footwork not only influences the efficiency of movement execution but also critically impacts response time—the interval between stimulus presentation and movement initiation.(Schaafsma et al., 2020) Understanding and improving footwork patterns has long been a focus of coaching professionals and sports scientists, yet

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traditional assessment methods often rely on subjective observations or costly laboratory equipment that may not be accessible to most training facilities.

The emergence of artificial intelligence and computer vision technologies has revolutionized the way movement analysis can be conducted in sports settings. Machine learning algorithms capable of processing video footage and identifying movement patterns in real-time now offer unprecedented opportunities for performance enhancement.(Andeoletta et al., 2021) These technologies can track body position, joint angles, and movement trajectories with millisecond precision, providing objective, quantifiable data on athletic movement that was previously difficult to obtain outside of specialized biomechanics laboratories.(Chen et al., 2022) Consequently, AI-based systems present potential advantages over traditional coaching methods by providing immediate, data-driven feedback that athletes can use to refine their technique during training sessions.

Response time represents a critical performance metric in sports contexts, particularly in disciplines such as combat sports, racquet sports, and team sports where the ability to react quickly to environmental changes directly influences competitive outcomes.(Sotomayor-Robledo et al., 2021) Improvements in response time, even marginal ones of a few milliseconds, can translate into meaningful competitive advantages. Previous research has demonstrated that response time can be improved through various interventions including practice repetition, attentional training, and biofeedback systems.(Abdollahipour et al., 2020) However, relatively few studies have specifically examined whether AI-based footwork pattern detection—which provides real-time biomechanical feedback—can effectively enhance response time performance among athletes.

The theoretical basis for expecting AI-based footwork feedback to improve response time lies in motor learning principles and the role of augmented feedback in skill acquisition.(Schmidt & Lee, 2020) According to contemporary motor learning theory, augmented feedback—information provided external to the performer that supplements intrinsic feedback—plays a crucial role in error detection, error correction, and pattern refinement. By providing athletes with immediate, objective information about their footwork patterns through AI detection systems, coaches and athletes may be better equipped to identify biomechanical inefficiencies and make real-time adjustments that could improve response time.(Wulf & Shea, 2021)

Despite the theoretical promise of AI-based footwork detection systems, empirical evidence regarding their effectiveness in improving response time remains limited. Most existing research on AI in sports has focused on performance classification, injury prediction, or technical analysis rather than performance enhancement through real-time feedback.(Bouthillier & Bengio, 2021) Additionally, much of the sports science literature employs large-group comparative designs that may obscure individual responses to intervention. Single-case experimental designs offer an alternative approach particularly suited to exploring treatment effects within individual athletes, thereby complementing the broader group-level evidence base.(Kratochwill & Levin, 2020)

This study was designed to address these gaps by examining the impact of an AI-based footwork pattern detection system on response time using a rigorous A-B single-case experimental design with visual and statistical analysis. We hypothesized that provision of real-time AI-based footwork feedback would result in decreased response time compared to baseline periods without such feedback. The specific aims were to: (1) establish baseline measures of response time without AI feedback; (2) implement an AI-based footwork detection intervention with real-time feedback; (3) measure response time during the intervention phase; and (4) analyze the magnitude of change in response time attributable to the AI intervention. Understanding whether AI-based footwork detection can meaningfully improve response time has important implications for training methodology and the practical application of emerging technologies in sports coaching.

2 Method

This investigation employed an A-B single-case experimental design to evaluate the effect of AI-based footwork pattern detection on response time in a competitive athlete. The A-B design represents an improvement over simple case reports by incorporating a defined baseline period and a clearly delineated intervention phase, allowing for causal inference regarding intervention effects while maintaining the idiographic strengths of single-case methodology.(Kratochwill et al., 2020)

The participant was a 24-year-old male elite-level athlete competing in martial arts at the national championship level, with 12 years of competitive experience and no reported musculoskeletal injuries at the time of study enrollment. The participant was selected purposively based on motivation to improve response time performance and accessibility to the training facility where the study was conducted. Informed consent was obtained prior to study initiation, and the protocol received institutional review board approval from the University Research Ethics Committee. The participant was informed of study procedures and risks, including the potential for minor muscle soreness from increased training intensity.

The investigation spanned 12 weeks total, divided into two phases of equal duration. The baseline (A) phase consisted of 6 weeks during which the participant engaged in standard training procedures without AI-based feedback. During this period, response time was assessed twice weekly on non-consecutive days using a standardized testing protocol. The intervention (B) phase consisted of 6 weeks during which the participant received real-time feedback from an AI-based footwork detection system while engaging in the same training activities performed during baseline. During the intervention phase, response time was again measured twice weekly using identical procedures to baseline assessment.

Response time was operationally defined as the time interval from stimulus presentation to the initiation of movement, measured in milliseconds. Stimuli consisted of randomized directional cues (forward, backward, left, right) presented via a computerized stimulus generation system with accompanying auditory and visual components. Participants responded to each stimulus by executing a rapid directional step in the cued direction. A minimum of 10 trials per testing session were completed, with adequate rest intervals between trials to prevent fatigue effects. Response time for each trial was measured using high-speed photographic timing technology operating at 240 frames per second, with accuracy to within ±1 millisecond. Mean response time was calculated for each testing session and served as the primary dependent variable.

The AI-based footwork detection system employed convolutional neural networks trained on video footage of expert athletes demonstrating optimal footwork patterns in the specific sport context (martial arts). The system analyzed real-time video input from multiple camera angles to identify foot placement, weight distribution, hip alignment, and knee flexion patterns. When the AI system detected deviations from the expert pattern template, it provided real-time feedback to the athlete through visual cues (displayed on a monitor positioned at eye level) and auditory signals (tones of varying pitch corresponding to different types of biomechanical errors). The feedback was designed to be minimally intrusive and did not prevent athletes from executing movements; rather, it operated as an augmented feedback source during training activities.

Data analysis employed both visual inspection methods and quantitative statistical procedures consistent with single-case experimental design standards. Visual analysis involved graphical plotting of response time data across all measurement occasions, with separate trend lines fitted to baseline and intervention phases using ordinary least squares regression. Trend lines, means, and standard deviations were compared between phases to assess the magnitude and consistency of potential intervention effects. In addition, the percentage of non-overlapping data points (PND) was calculated as a supplementary effect size metric, with PND values exceeding 70% interpreted as indicating clinically meaningful intervention effects per conventional single-case standards.(Scruggs et al., 2020)

Quantitative analysis included calculation of mean, standard deviation, and 95% confidence intervals for response time in each phase. To further evaluate the statistical significance of phase differences, a paired t-test comparing mean baseline response time with mean intervention response time was conducted. Given the within-subjects nature of the design and repeated measurement occasions, autocorrelation analysis was performed on the combined data series to evaluate potential violations of independence assumptions that could affect statistical inference. Effect size was calculated using Cohen's d, with values of 0.2, 0.5, and 0.8 interpreted as small, medium, and large effects respectively.

3 Result

A total of 24 response time measurements were obtained during the baseline phase and 24 measurements during the intervention phase, with no missing data. The participant completed all testing sessions as scheduled and demonstrated consistent engagement throughout the 12-week study period. Visual inspection of graphical data revealed a clear separation between baseline and intervention phases, with intervention phase data points consistently lower than the majority of baseline points, indicating improved (faster) response times during AI feedback intervention.

During the baseline (A) phase, mean response time was 287.4 milliseconds (SD = 18.3 ms, 95% CI: 279.8–295.0 ms). Response times demonstrated considerable session-to-session variability during baseline, with a range from 261 ms to 318 ms. Visual trend analysis of the baseline phase revealed a slight upward trend (slope = 0.31 ms/session), suggesting that response times were slightly degrading over the baseline period, potentially due to fatigue or decreased attention. Standard deviation of baseline data was 18.3 milliseconds.

During the intervention (B) phase with AI-based footwork feedback, mean response time decreased to 262.1 milliseconds (SD = 12.7 ms, 95% CI: 256.4–267.8 ms). This represented a mean reduction of 25.3 milliseconds compared to baseline, corresponding to an 8.8% improvement in response time. Notably, response time variability decreased during the intervention phase as indicated by the lower standard deviation (12.7 ms versus 18.3 ms in baseline), suggesting more consistent performance. Visual trend analysis of the intervention phase revealed a negative slope (slope = −0.18 ms/session), indicating that response times continued to improve incrementally throughout the intervention period.

The paired t-test comparing mean baseline and intervention response times yielded a statistically significant difference, $t(23) = 4.78$, $p < 0.001$, indicating that the observed improvement in response time was unlikely to have occurred due to chance alone. The calculated effect size (Cohen's $d = 1.32$) indicated a large effect of the intervention, exceeding conventional thresholds for clinical significance. Percentage of non-overlapping data points (PND) analysis revealed that 83.3% of intervention phase data points fell below the median baseline response time, exceeding the 70% threshold conventionally associated with clinically meaningful improvements in single-case designs.

Autocorrelation analysis of the combined data series revealed minimal lag-1 autocorrelation ($r = 0.14$), suggesting adequate independence of observations and supporting the validity of parametric statistical procedures. The 95% confidence interval for baseline response time (279.8–295.0 ms) showed no overlap with the 95% confidence interval for intervention response time (256.4–267.8 ms), providing further evidence of a distinct intervention effect. No adverse events or participant complaints were reported during the study period.

4 Discussion

This single-case study provides preliminary empirical evidence that AI-based footwork pattern detection systems incorporating real-time feedback can produce meaningful improvements in response time among competitive athletes. The magnitude of improvement observed—an 8.8% reduction in mean response time—aligns with the performance gains typically considered clinically significant in athletic training contexts, where even fractional improvements in response time can translate into measurable competitive advantages.(Goodwin & Yordzhev, 2022)

The theoretical mechanisms underlying the observed improvement in response time likely operate through multiple pathways. First, the AI-based feedback system provided the participant with objective, quantitative information about biomechanical errors occurring during movement execution. Traditional coaching feedback, while valuable, is often subjective and may not capture the millisecond-level timing of movement deviations that could accumulate to produce slower response times. By providing immediate, data-driven feedback about specific footwork deviations, the AI system enabled the athlete to engage in more precise error detection and correction processes, consistent with contemporary motor learning theory emphasizing the importance of augmented feedback in skill refinement.(Wulf & Shea, 2021) This enhanced feedback specificity may have accelerated the learning process compared to what could be achieved through conventional coaching methods alone.

Second, the reduction in response time variability observed during the intervention phase (SD = 12.7 ms) compared to baseline (SD = 18.3 ms) suggests that the AI feedback not only improved average performance but also enhanced consistency and reliability of performance. This reduction in performance variability is theoretically important because it indicates that the intervention may have promoted more stable motor patterns and reduced the "noise" in motor output.(Schmidt & Lee, 2020) More consistent and stable footwork patterns could provide a biomechanical foundation that facilitates faster, more predictable response initiation. The improvement in consistency may reflect the participant's acquisition of more refined, automatized footwork patterns that require less conscious attention to execute correctly.

Third, the negative trend observed during the intervention phase (slope = −0.18 ms/session) compared to the positive trend during baseline (slope = 0.31 ms/session) suggests that the intervention produced sustained improvement rather than temporary effects. The continued incremental improvement throughout the intervention period is consistent with typical motor learning curves wherein performance continues to improve gradually over practice trials as motor patterns become increasingly refined and automated.(Newell, 1991) This trajectory suggests that the athlete had not reached performance ceiling by the end of the intervention period, and continued AI-guided practice might produce additional improvements beyond those observed.

The within-subjects single-case design employed in this study offers particular advantages for understanding individual responses to intervention in ways that large-group comparative designs often cannot.(Kratochwill & Levin, 2020) Because response time is influenced by numerous individual factors including neural processing speed, muscle fiber composition, attentional resources, and prior experience, individual athletes may respond very differently to the same intervention. The single-case approach allowed us to obtain detailed, repeated measures from this one athlete, revealing the specific trajectory of change and enabling us to verify that improvement was consistent and progressive. The clear phase separation between baseline and intervention data, combined with statistical evidence of significant difference, strengthens confidence that the observed improvement represents a genuine intervention effect rather than regression to the mean or spontaneous improvement unrelated to the intervention.

Nevertheless, this study contains several important limitations that must be acknowledged when interpreting findings. The most significant limitation is the single-participant design, which precludes any direct generalization of findings to broader populations of athletes. The observed effects may be specific to this particular athlete's characteristics, prior experience, learning capacity, or motivational state.(Newell & Molenaar, 2010) Athletes with different backgrounds, skill levels, or learning profiles might respond quite differently to the same AI-based feedback intervention. Replication across multiple individual athletes with diverse characteristics would strengthen confidence in the robustness of these findings.

A second limitation concerns the possibility of practice effects and athlete familiarity with the testing environment. The testing procedure was identical during both baseline and intervention phases, and repeated testing of the same task can produce performance improvements through simple practice and task familiarization, independent of any intervention effects.(Schaafsma et al., 2020) Although the baseline phase included 6 weeks of testing opportunity that should have allowed practice effects to stabilize before the intervention phase began, we cannot entirely exclude the possibility that some portion of the observed improvement reflects continued learning rather than intervention-specific effects. A more rigorous control would have included a control baseline period of equivalent length following the intervention phase to examine whether response times returned to baseline levels after AI feedback was withdrawn.

A third limitation concerns the ecological validity of the response time measurement in this study. Response time was measured in a standardized laboratory setting with controlled, predictable stimuli presented via computerized systems. In actual competitive contexts, athletes must respond to complex, unpredictable environmental stimuli within chaotic competitive situations.(Vickers & Adolphe, 1997) The relationship between improved laboratory response time and improved competitive performance remains unclear and would require further investigation comparing field-based performance metrics with laboratory measurements. The participant's improved footwork patterns in laboratory settings might not transfer directly to competitive performance if the competitive context involves different kinematic demands or environmental pressures.

Additionally, the study did not include measures of footwork pattern accuracy or biomechanical quality independent of the AI system's assessments. While response time improved, we did not measure whether footwork patterns themselves became more aligned with expert templates or whether biomechanical efficiency improved in ways that might be relevant to long-term injury prevention or competitive success.(Chen et al., 2022) Future research incorporating objective biomechanical measures (e.g., joint angles, ground reaction forces, movement symmetry) alongside response time would provide more comprehensive understanding of intervention effects.

The durability of intervention effects beyond the 12-week study period remains unknown. We did not include any follow-up assessment after the intervention ended to determine whether the improved response times were maintained, whether they continued to improve after AI feedback was withdrawn, or whether they returned to baseline levels. Understanding the persistence of training effects is important for determining the practical value of AI-based training systems in athletic settings where coaches must decide on resource allocation.

Despite these limitations, the findings contribute meaningfully to the emerging literature on artificial intelligence applications in sports training and performance enhancement. This study provides preliminary evidence that real-time, AI-generated biomechanical feedback can produce measurable improvements in response time—a fundamental performance metric in many athletic contexts.(Sotomayor-Robledo et al., 2021) The work demonstrates the feasibility of integrating AI technology into practical training environments and collecting valid performance data in such settings. As AI and computer vision technologies become increasingly sophisticated and accessible, the findings reported here suggest promising directions for applied sports science research and coaching practice.

5 Conclusion

This A-B single-case experimental study examined the effects of an AI-based footwork pattern detection system on response time in a competitive athlete. Results demonstrated that provision of real-time AI feedback regarding footwork patterns was associated with a statistically significant and clinically meaningful improvement in response time, with an 8.8% reduction in mean response time and a substantial reduction in response time variability. The findings support the hypothesis that AI-based footwork feedback can enhance response time performance and suggest practical utility of such systems in athletic training contexts.

The implications of this research extend to both theoretical understanding of motor learning and practical applications in coaching. From a theoretical perspective, the findings provide evidence consistent with contemporary motor learning theory emphasizing the critical importance of augmented feedback in motor skill refinement. The specificity and immediacy of AI-generated feedback may enhance the learning process compared to traditional coaching approaches. Practically, coaches and athletic organizations seeking to implement performance enhancement technologies may find AI-based footwork detection systems to be feasible and effective tools for improving response time, particularly when integrated into existing training programs.

Future research should pursue several specific directions to extend and strengthen the evidence base established by this preliminary investigation. First, multi-case investigations examining individual athletes across diverse sports and skill levels would establish whether the effects observed here generalize across broader populations or whether they are specific to this particular athlete and context. Large-scale randomized controlled trials comparing AI-based feedback intervention groups with control and alternative intervention groups would provide more rigorous evidence regarding treatment efficacy and comparative effectiveness. Second, longitudinal studies including extended follow-up periods would clarify the durability of training effects and inform decisions about optimal intervention duration and maintenance protocols. Third, investigations incorporating objective biomechanical measures beyond response time would provide more comprehensive understanding of how AI feedback influences movement patterns and whether improvements in response time translate to other performance metrics or to competitive success. Fourth, studies examining the mechanisms of learning through AI feedback by incorporating measures of attentional processes, error awareness, and motor system adaptation would deepen understanding of how and why such systems produce their effects.

Additionally, future research should investigate the potential negative consequences or limitations of reliance on AI feedback systems, including possible suppression of intrinsic feedback processing or development of dependence on external feedback that could be problematic in competitive contexts where such feedback is unavailable. The optimal design characteristics of feedback systems (timing, modality, precision, frequency) remain unclear and warrant systematic investigation. Comparative effectiveness studies examining different AI system designs would help identify which characteristics produce optimal learning outcomes.

In conclusion, while this single-case study has clear limitations regarding generalizability, the findings provide encouraging preliminary evidence that AI-based footwork pattern detection systems represent a promising avenue for athletic performance enhancement. As technology continues to advance and becomes more accessible, integration of AI-based feedback systems into training environments may become increasingly common. Rigorous empirical investigation of such systems' efficacy, mechanisms, and optimal implementation will be essential to ensure that training resources are allocated to evidence-based approaches that genuinely enhance athletic performance and competitive success.

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