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CyberCoach: a Wearable Biofeedback System for Runners

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***Abstract*— Wearable technologies are increasingly being used to help runners improve their performance and reduce the risk of injuries. While off-the-shelf devices are typically limited to interval-based cueing and post training analysis, the emerging wearable biofeedback systems (WBSs) can provide closed-loop feedback during training. However, most existing WBSs for runners are inaccurate for real-time spatiotemporal gait analysis, limited to temporal gait parameters, or not suitable for out-of-the-lab use. This paper introduces a novel WBS that leverages on-line gait analysis capabilities and continuous music modulation to elicit a target time-varying running speed on the wearer. We compared the effectiveness of two alternative auditory feedback strategies (play-back rate modulation – PRM, noise amplitude modulation – NAM) against a conventional training strategy (running watch discrete alarms – WA), in terms of stride-by-stride velocity errors in a group of competitive and recreational runners, using an out-of-the-lab High-Intensity Interval Training (HIIT) protocol. Results indicate that PRM and NAM may elicit significantly better adherence to both low and high-intensity target velocities compared to WA. NAM outperformed PRM in terms of velocity errors, but participants found the latter modality to be more enjoyable. Overall, these results highlight the potential of WBS and continuous music modulation as effective means to provide accurate, granular, and meaningful feedback to runners, and pave the way for future studies focusing on the long-term training effects of this technology.**

***Index Terms*— Wearable Technology, Biofeedback, Instrumented Footwear, Human-in-the-loop Control, Gait Analysis.**

I. Introduction

Running is a popular sport for both recreational and competitive endeavors. In 2017, approximately 60 million Americans participated in running or jogging [1]. Correcting form, modifying cadence and foot landing, and training to improve running economy are all significant steps towards improving running performance [2]. However, the current training methods to improve performance, which consist of personal or technology-based coaching, remain either inaccurate or expensive. Personal coaches can provide constructive feedback conducive to a runner's progression, however they are not accessible to most runners due to their sheer costs, and results largely depend on the coach's expertise and ability to create a personalized training plan, ever-changing with an individual's progress [3]. Technology-assisted coaching includes off-line gait-analysis systems [4], running parameter cueing [5], or closed-loop feedback methods and devices [6]. Wearable systems for gait analysis, such as instrumented insoles, can accurately record gait metrics and provide the summary performance data post-training, through a phone application. However, they are often restricted to off-line analyses [4]. Consumer-grade running watches and mobile applications are more affordable than instrumented insoles. They can measure running speed, cadence, and step count and also provide interval target cueing. However, running watches are often inaccurate, especially within smaller radii of operation or GPS-denied environments [5]. Moreover, the cues provided by those devices cannot self-adjust to changes in the wearer's performance.

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Emerging biofeedback systems are capable of providing both on-line gait analysis and closed-loop visual, haptic, or auditory feedback modulated by the errors between a measured running metric and a predefined target value. Visual feedback devices utilize a screen to deliver feedback to runners. Depictions of graphs [7], colors [8], or shapes [9]–[11] are projected to allow the runner to react and understand what needs to change in their running style [7], [9], [10], performance, and foot loading patterns [8], [11]. Most systems based on visual feedback rely on a fixed screen or monitor [7], [8], [10], [11]. Training through this method has been shown to be effective in a laboratory setting, especially in the short-term. However, this modality is dependent on an obtrusive screen, making it less applicable to out-of-the-lab environments.

Haptic-based wearable biofeedback systems (WBSs) provide the runner with augmented somatosensory feedback through vibrations or resistive forces to modify running biomechanics. Vibrotactile feedback has been integrated with running watches, whereby vibrating motors were controlled on-line using custom software, to reduce peak tibial acceleration [12]. Resistive feedback was implemented on a belt instrumented with cables applying resistive forces to the legs [13]. The feedback, calculated from inertial measurement units (IMUs), was shown to be effective at modifying sagittal-plane kinematics and cadence, to minimize tibial stresses [13]. Because haptic-based WBSs are minimally invasive and relatively affordable, they can be easily deployed in out-of-the-lab environments [12]. However, evidence of the effectiveness of somatosensory feedback as a training method for runners is still very limited [6].

Auditory-based WBSs provide prescriptive or descriptive feedback in the form of discrete audio signals, such as metronome beats and prerecorded cues, or continuous music modulation. Auditory beeps or metronome beats have been used to indicate if a target value is not being met. In these methods, pitch variation is usually employed to enable bidirectionality [11], [14], [15]. Using inputs from accelerometers or IMUs, these modalities have proven successful in helping the wearer modify their running biomechanics, e.g., alter their peak positive tibial or foot acceleration, which are surrogate measures of impact force [11], [14], [15]. In [7], prerecorded verbal instructions were used to cue the runner to reduce the vertical displacement of the body center of mass and the stride frequency, showing significant immediate effects (20% and 10% reductions, respectively). In [16], a phone application was developed to deliver directional prerecorded cues every 5 seconds, to help the wearer adjust their running speed towards a predetermined target pace. While results indicated that auditory cueing was more effective than traditional mental tracking [16], the accuracy of the device in estimating running speed was not evaluated, the feedback modality did not provide the wearer any information about their current running speed, and the experimental protocol only explored relatively slow speeds (i.e., 1.9 m/s - 2.7 m/s) that are not representative of high-intensity exercises. Unlike discrete prerecorded cues, continuous music modulation takes an existing sound track and modifies the track's parameters (playback rate, volume, pitch, etc.) on-the-fly, according to the wearer's performance. While this method has been successfully integrated with WBSs for runners, most studies are limited to modulating the wearer's cadence based on the music tempo [17], [18], and no research to date has investigated the use of continuous music modulation to elicit a target running speed on the wearer in out-of-the-lab settings.

This paper introduces a novel auditory-based WBS for runners called *CyberCoach*. The CyberCoach consists of custom-engineered instrumented insoles, a single-board computer embedded in a running belt, and running earbuds to provide closed-loop auditory feedback to help the wearer adjust their running speed to a target pace. To the best of the authors' knowledge, the CyberCoach is the first WBS capable of accurately estimating stride-by-stride running speed in real-time, while providing intuitive feedback to help the runner to maintain a time-varying target velocity. In this study, we validate the device by comparing the immediate effects of two alternative auditory feedback modalities (playback rate modulation – PRM, noise amplitude modulation – NAM) against a conventional training strategy (running watch discrete alarms – WA), in terms of stride-by-stride velocity errors during a simulated High-Intensity Interval Training (HIIT) protocol. The remainder of this paper is organized as follows. Section II describes the CyberCoach; Section III details the experimental protocol; Sections IV and V present the statistical analysis and results, respectively; and Section VI covers the discussion and conclusions.

II. System Description

The CyberCoach consists of custom-designed instrumented insoles with shoe-mounted logic units, a Linux single-board computer, and a pair of running earbuds (Fig. 1). The software architecture of the CyberCoach includes online gait analysis module, offline music track selection module, and closed-loop biofeedback engine with remote control capability through a custom graphical user interface (GUI). The following sections describe the hardware and software modules of the CyberCoach system.

Fig. 1. The *CyberCoach* consists of **(A)** Custom-engineered instrumented insoles (*SportSole*) featuring embedded IMU **(A_1)**, FSR array **(A_2)**, and logic units; **(B)** a running belt with embedded single-board computer **(B_1)**, Li-Po battery, and miniature Wi-Fi router **(B_2)**; **(D)** sport earbuds to deliver the auditory feedback. An off-the-shelf running watch **(C)** was used for comparison, but it is not part of the proposed system.

A. Hardware

The instrumented insoles build upon the *SportSole*, a device developed in the Wearable Robotic Systems Laboratory at Stevens Institute of Technology [19]–[21]. Each insole is equipped with a 24g inertial measurement unit (IMU, Yost Labs Inc., OH, US) and an 8-cell array of force sensitive resistors (FSR). The IMU is placed under the medial arch of the foot. The FSR array (IEE S.A., Luxemburg) measures ground reaction forces under the calcaneous, lateral arch, heads of the metatarsals, toes, and hallux. All sensors are pancaked together using anti-abrasion, flexible foam.

The custom-designed logic modules are each mounted on the lateral collar of the subject's footwear via plastic clips. Each logic module is safely enclosed in 3D printed boxes. It consists of a custom-designed PCB and programmable μ-controller (32-bit ARM Cortex-M4, PJRC, OR, USA) powered by a small Li-Po battery. These on-board logic units extract stride-by-stride gait parameters from raw sensors data using the methods described in [19], [21] and transmit these metrics to the Linux single-board computer through a UDP network via WLAN, as described in Sec. II-B.

The single-board computer is a 64-bit ARM v8 quad-core CPU (Hardkernel, GyeongGi, South Korea) that fits inside a running pouch fashioned on the subject's waist. A miniature

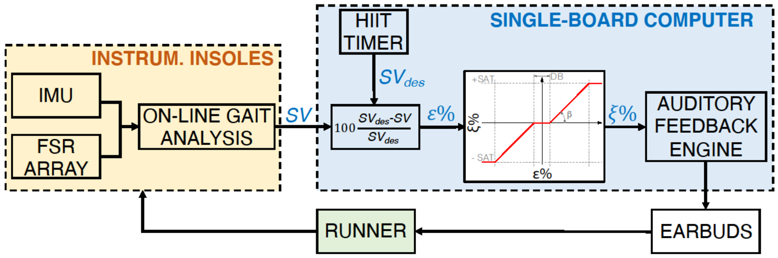

Fig. 2. System architecture: The HIIT timer determines the target running speed $SV_{des} \in [SV_L, SV_H]$ based on the elapsed time. Stride-by-stride normalized velocity errors $\varepsilon\%$ are converted to feedback inputs $\xi\%$ through a linear map with adjustable slope β, dead-band (DB) and saturation (SAT) and fed to the auditory feedback engine that delivers continuous stimuli to the runner through earbuds.

Wi-Fi router connected to the single-board computer is also embedded in the running pouch and serves as an access point for the WBS. The single-board computer serves as a datalogger to store stride-by-stride gait parameters as well as raw sensor data (333 Hz). It also runs the algorithms responsible for the auditory feedback modulation, as described in Sec. II-D. Running earbuds connected to the single-board computer deliver the auditory stimuli to the wearer.

While the CyberCoach may work as a stand-alone, fully-portable system, the Wi-Fi connection allows the experimenter to adjust the biofeedback parameters and enable/disable the device remotely, using a laptop.

B. On-line Spatiotemporal Gait Analysis

The gait analysis capabilities of the insole system for walking and running tasks were developed and validated in previous works [19], [21]. In short, CyberCoach's estimates of stride time (ST) are computed on-line based on FSR signals, from which the timing of initial contacts and toe-off events are also derived. Stride-by-stride estimates of stride length (SL) are also computed on-line, by first removing the contribution of gravity from the accelerometer readings (i.e., by means of orientation estimates obtained with an Extended Kalman Filter), followed by double integration of accelerometric signals with zero-velocity-updates (ZUPT) and velocity drift compensation (VDC), as detailed in [22]. At each stride, stride velocity (SV) is determined as the ratio between SL and the corresponding ST. The calculated SV is transmitted to the Linux computer over UDP, for datalogging and for use in the biofeedback engine.

C. Personalized Music Track Selector

Before a training session takes place, the wearer's natural running cadence and their stride-to-stride variability must be estimated, to match their natural rhythms to the tempo of a music track and set an appropriate dead-band for the auditory stimuli. To this end, the wearer's average natural cadence (CAD) and the standard deviation of their stride velocity (SD_{SV}) are estimated offline, after a baseline running session is collected with the CyberCoach (set to no-feedback mode). CAD is estimated as the dominant frequency of the sum of all FSR signals, restricted to the interval 2-3.5 Hz and converted to steps per minute [23]. To obtain SD_{SV} we apply detrended fluctuation analysis (DFA) to the stride-by-stride SV time series and calculate the standard deviation of the resulting detrended series [24]. This approach can capture the approximate stride-to-stride variability while filtering out any effect due to local changes in the mean stride. As described in Sec. II-D, SD_{SV} determines the maximum velocity errors that are regarded as *acceptable* during a training exercise. To mitigate unwanted gait retraining due to conflicting rhythms [18], and to further personalize the feedback modality, the estimated CAD is used to select a music track that approximately matches the runner's rhythm. To this end, we developed a song database sorted by music genre and tempo (beats per minute, BPM). The tempo and tempo variability of each song were estimated using beat tracking methods [25]. Candidate music tracks whose tempo variability exceeded a predefined threshold were automatically excluded from the database. The total number of music tracks included in the final database exceeded 75 songs. A custom Matlab script uses the runner's CAD and favorite music genre as inputs, and outputs a list of music tracks within the chosen music genre, whose tempo is within 10% of the runner's CAD, sorted by lowest to highest absolute percent difference between the runner's CAD and the music tempo. Participants are then asked to choose a song from the list, based on their personal preference.

D. Auditory Feedback Engine

The biofeedback engine runs on the Linux single-board computer. It consists of a lower-level software module and a high-level sound synthesis engine. The former is responsible for computing stride-by-stride SV errors and for logging the insole data for off-line processing. When initializing the system, the lower-level module receives the target SV values for the next training session and SD_{SV} as inputs. During operation, the wearer's stride-by-stride SV measured by the insoles is compared with the target speed SV_{des} to calculate the percent error $\varepsilon_{\%}$, which is then sent to the sound synthesis engine through a local UDP socket.

At the higher level, sounds are generated through an open source visual programming language for multimedia (Pure-Data, [26]). This software was chosen for its compatibility with ARM-based devices and real-time sound-synthesis capability [27]. The sound synthesis module converts the error $\varepsilon_{\%}$ to a corresponding feedback signal $\xi_{\%}$ according to a linear map with adjustable slope, dead-band, and saturation point, Fig. 2. In turn, $\xi_{\%}$ controls the auditory stimuli according to one of the following feedback modalities:

1) Playback Rate Modulation (PRM): PRM changes the pitch of a music track bidirectionally, trending directly with playback rate [17], [18]. In our implementation, PRM is achieved by modifying the original sampling rate of a music track (44.1 kHz) on-the-fly, so that a positive $\xi_{\%}$ (indicating that the wearer is running too fast) results in a corresponding % increase of playback rate, and vice versa.

2) Noise Amplitude Modulation (NAM): NAM is achieved through the overlay of white noise onto a music track. The amplitude of the noise relative to the music track volume is determined by $|\xi_{\%}|$. The sign of the velocity errors is rendered through sound spatialization, whereby a positive (negative) $\xi_{\%}$ affects the noise volume delivered to the right (left) ear.

The CyberCoach is controlled remotely via a Matlab GUI, which allows the experimenter to configure the auditory feedback parameters (volume, music track selection, width of dead-band, saturation point, and slope of the linear mapping), initialize the WBS, and activate the data-logger. The GUI also enables the experimenter to record the audio heard by the wearer for offline analysis. In our implementation, a unitary slope was selected between $\varepsilon_{\%}$ and $\xi_{\%}$ for simplicity, the width of the dead-band was set to $2\,\mathrm{SD_{SV}}$ such that small velocity errors falling within $\pm 1\,\mathrm{SD_{SV}}$ would not produce alterations in the auditory stimuli, and the saturation point was determined empirically during preliminary tests, so that large velocity errors would not result in excessively unpleasant auditory stimuli.

III. Experimental Protocol

A total of 8 young adults (age: 23 $\pm$ 5 years, height: 164.8 $\pm$ 21.5 cm, weight: 69.2 $\pm$ 4 kg, 7 males) volunteered for this study, which was designed to compare the immediate effects of PRM and NAM (CyberCoach auditory feedback strategies) relative to running watch discrete alarms (conventional method, WA) in terms of SV errors, during a simulated HIIT protocol. Prospective participants were included if they were recreational or competitive runners who ran at least 15 km per week. The protocol was approved by the Stevens Institutional Review Board and all subjects gave written informed consent prior to the experimental sessions.

After fitting the CyberCoach and an off-the-shelf running watch (Garmin Forerunner 35), each subject was asked to perform the 800-meter run test at their best pace (baseline running bout, BL), followed by a 5-minute break (Fig. 3). During the break, the experimenter extracted the participant's CAD and $\mathrm{SD_{SV}}$ following the methods outlined in Sec. II-C, and calculated the target training speeds for the HIIT protocol, which were indicated as $\mathrm{SV_H}$ and $\mathrm{SV_L}$ (high- and low-intensity training speed, respectively). The HIIT paradigm alternates a rapid sequence of high- and low-intensity running bouts. It was selected because of its effectiveness in improving running economy, peak speed, and VO2 max of both recreational and competitive runners [28]–[32]. $\mathrm{SV_H}$ and $\mathrm{SV_L}$ were determined from the time of the 800-meter run test through a widely used training pace calculator [33], by setting the target paces to *interval* and *marathon*, respectively.

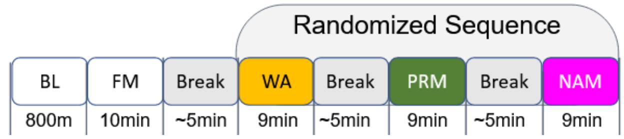

Fig. 3. Experimental Protocol. BL = Baseline bout, FM = Familiarization bout, WA = Watch Alarms, PRM = Playback Rate Modulation, NAM = Noise Amplitude Modulation. Each feedback modality was tested over a total of 3 repetitions of low- and high-intensity running bouts.

Subsequently, the subject was allowed to familiarize with each feedback modality (WA, PRM, NAM) for a total of 10 minutes (familiarization bout, FM). The saturation point and slope of the linear mapping for both PRM and NAM were set to the same values for all participants. The WA consisted of vibratory cues informing the wearer that his/her pace was not being kept at the target value. This modality was included in the protocol as representative of conventional technology-based training methods for runners. However, because WA simply indicates a discrepancy between the current and the target running speed, without regard to the magnitude and directionality of the error, we expected this modality to be the least effective one. After FM, participants underwent three HIIT bouts, each corresponding to a feedback modality. Each HIIT bout consisted of three repetitions of low- and high-intensity running, for a total of 9 minutes per HIIT bout. Within each repetition, the target speed $\mathrm{SV_{des}}$ was set at $\mathrm{SV_L}$ for the first 110 seconds, followed by a 10-second ramp up period to $\mathrm{SV_H}$. $\mathrm{SV_{des}}$ was then maintained at $\mathrm{SV_H}$ for 50 seconds, after which a 10-second ramp down period brought it back to $\mathrm{SV_L}$. The sequence of the feedback modalities (WA, PRM, NAM) was assigned to participants using a Latin square design. To mitigate effects of fatigue, participants were required to rest for at least 5 minutes in-between the HIIT bouts. All running tests were conducted in an outdoor flat area. The length of the running perimeter was approximately 400m.

IV. Statistical Analysis

To compare the immediate effects of the three feedback modalities on the wearer's running gait we computed steady-state mean absolute errors (MAE) in SV from each study participant, for each modality, separately for low- and high-intensity intervals. To approximate steady-state conditions, only the last 60 seconds of the low-intensity intervals and the last 30 seconds of the high-intensity intervals were included in the analysis. For each participant, MAE was defined as the average of the stride-by-stride absolute difference between the subject's current running speed (SV) and the corresponding target speed ($\mathrm{SV_L}$ or $\mathrm{SV_H}$).

A two-way repeated measure ANOVA was carried out to check for significant ($\alpha = 0.05$) effects of feedback modality (WA, PRM, NAM) and training intensity (low vs. high intensity) on the MAE, as well as potential interactions between the two factors. Mauchly's test was applied to check sphericity, and the Huynh-Feldt correction was applied if Mauchly's test indicated that the assumption of sphericity had been violated. When significant effects were identified,

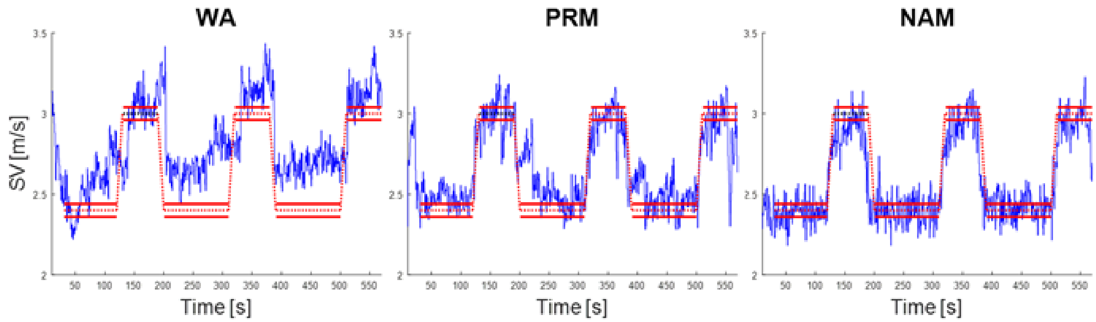

Fig. 4. Data from a representative participant, showing the time history of SV for the three feedback modalities. Red lines indicate the target training speed SV_{des} (dashed lines) as well as the associated dead-bands (solid lines).

post-hoc comparisons using the Bonferroni-Holm correction were applied as appropriate.

V. Results

Participant's baseline metrics were 167.1 $\pm$ 8.5 steps/min (mean $\pm$ SD) and 0.042 $\pm$ 0.010 m/s for CAD and SD_{SV}, respectively. SV_L ranged from 2.33 to 3.12 m/s (2.69 $\pm$ 0.28 m/s, mean $\pm$ SD) and SV_H ranged from 2.85 to 3.81 m/s (3.38 $\pm$ 0.34 m/s). Figure 4 shows the stride-by-stride SV of a representative participant for the three feedback modalities, along with SV_{des} and the corresponding dead-bands. Figure 5 shows the group averages of MAE. The MAE was significantly larger for the high-intensity task than it was for the low-intensity task (principal effect of training intensity, p<0.05). However, kinematic errors varied with the feedback modality, regardless of training intensity (principal effect of feedback modality, p<0.001). Post-hoc analysis evidenced that WA resulted in significantly larger MAE compared to both PRM and NAM (corrected p<0.05 for both), while NAM resulted in smaller errors than PRM (corrected p<0.05). No significant interaction was found between training intensity and feedback mode.

VI. Discussion and Conclusion

This work introduced the CyberCoach, a minimally obtrusive WBS designed to help runners improve their running speed performance in out-of-the-lab environments. The CyberCoach leverages validated instrumented insoles [19]–[21] and a new auditory feedback engine to capture real-time SV and deliver auditory stimuli modulated by the deviations between the wearer's current running speed and a target training speed. Unlike similar WBSs for runners, the CyberCoach is capable of accurately estimating stride-by-stride running speed in real-time, while providing intuitive feedback to help the runner adjust their speed to a time-varying target velocity.

Experimental results suggest that the CyberCoach can promote better adherence to both low- and high-intensity running speeds compared to an off-the-shelf running watch. We argue that this improved efficacy is due to the system's stride-by-stride granularity in modulating the feedback provided to the wearer, as opposed to the WA's discrete cueing. This is in line with previous studies that evidenced the benefits of continuous and intuitive feedback modalities compared to discrete (interval-based) cueing [7], [8], [11], [14], [15], [17], [18]. NAM was the most effective among the 3 feedback strategies, possibly due to its straightforward nature, which made it easily discernible regardless of the magnitude of the errors. Indeed, in post-training surveys, the study participants rated the NAM as the most intuitive modality. This result is in line with [17], which used a similar noise-based auditory strategy to elicit changes in runners' cadence. PRM promoted significantly increased adherence compared to WA, however performed worse than NAM. We explain this result by noting that the performance of PRM was likely dependent on the subject's familiarity with the music track, and their ability to detect, interpret, and recall small variations in playback rate and pitch. Nonetheless, the PRM modality was rated as the most enjoyable one by the study participants. In line with [16], the auditory feedback was able to elicit desired speed modifications during HIIT sessions. However, unlike [16], our HIIT protocol was more challenging, being designed upon training tools that are commonly used by competitive and recreational runners [33]. Moreover, although we tested the effectiveness of PRM and NAM in terms of running speed adaptations, those feedback modalities lend themselves to other gait metrics (e.g., cadence, peak foot accelerations, and foot loading patterns), since the input to the biofeedback engine is a normalized error parameter.

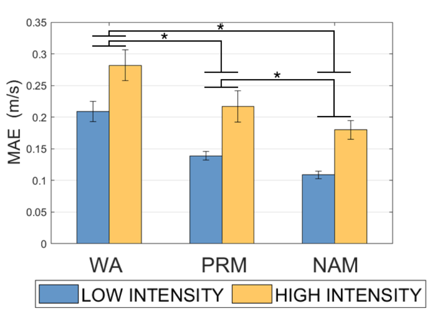

Fig. 5. Group averages of the Mean absolute errors (MAE) in stride velocity, for different training intensities and feedback modalities. Error bars indicate $\pm$ SE. $*$ indicate $p < 0.05$.

This preliminary study has several limitations. First, the small homogeneous sample does not allow us to draw any conclusions about the benefits of this technology for the general populations of competitive and recreational runners. Second, the study focused on immediate effects of augmented auditory feedback, as opposed to long-term training effects that are critical for competitive runners. Third, the study investigated unimodal feedback strategies, which limited the amount of information that could be provided to the wearer [34]. Future research is warranted to explore how multimodal strategies may overcome this problem and help runners adjust multiple biomechanical parameters concurrently [6]. Future work should also compare the effectiveness of continuous auditory and haptic feedback modalities for runners, and develop new adaptive feedback strategies that better conform to the wearer's evolving running performances.

VII. Acknowledgements

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