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Abstract

Purpose: This study aimed to independently validate a wearable inertial sensor designed to monitor training and performance metrics in swimmers.

Methods: Four male (21 ± 4 y, one national, three international) and six female (22 ± 3 y, one national, five international) swimmers completed 15 training sessions in an outdoor 50-m pool. Swimmers were fitted with a wearable device (TritonWear®, nine-axis inertial measurement unit with tri-axial accelerometer, gyroscope, and magnetometer), placed under the swim cap on top of the occipital protuberance. Video footage was captured for each session to establish criterion values. Absolute error, standardised effect and Pearson's correlation coefficient were used to determine the validity of the wearable device against video footage for total swim distance, total stroke count, mean stroke count, and mean velocity. Fisher's exact test was used to analyse the accuracy of stroke type identification.

Results: Total swim distance was underestimated by the device relative to video analysis. Absolute error was consistently higher for total and mean stroke count, and mean velocity, relative to video analysis. Across all sessions, the device incorrectly detected total time spent in backstroke, breaststroke, butterfly, and freestyle by 51 ± 15%. The device did not detect time spent in drill. Intraclass correlation coefficient results demonstrated excellent intra-rater reliability between repeated measures across all swimming metrics.

Conclusions: The wearable device investigated in this study does not accurately measure distance, stroke count, and velocity swimming metrics, or detect stroke type. Its use as a training monitoring tool in swimming is limited.

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Introduction

Athlete training load is routinely monitored by coaches and sport scientists to understand individual responses to the training stimuli, and to inform training prescription.[1] Training monitoring is additionally used to assess fatigue and recovery status, and to reduce the risk of developing non-functional overreaching, injury, and illness.[1] An array of monitoring devices and methods are available to assess the external (e.g., global positioning systems; GPS) and internal (e.g., rating of perceived exertion) load experienced by an athlete during training.[2]

External load (i.e., objective assessment of work performed) measures are commonly used to inform training prescription.[1,2] Accelerometer and GPS-based analysis of athletic performance are common in numerous land-based sports to assess external load.[1,3] However, the use of such devices within the aquatic environment presents many challenges, including the need for airtight sealing of sensors and ports, ambiguous validity of device positioning, and requirement for a reliable method to mount the device on the athlete.[4] Assessment of an athlete's external load allows objective quantification of movement (i.e., position, time, speed, and direction) during training.[3] Traditionally, video analysis is used within swimming as the gold standard criterion,[5] to quantitatively measure various swimming metrics (e.g., stroke count, velocity, and technical proficiency).[4,6] However, video analysis is laborious, does not allow real-time feedback, and is limited by turbulence and parallax error at the water-air interface.[4,6] Recent advancements in wearable technologies have sought to overcome these limitations, however further validation of the swimmer metrics is required.[2,3,5-7]

Previous research suggests there is a wearable device that is capable of measuring swim training and performance metrics.[5] However, this study only assessed the validity of freestyle and breaststroke over a distance of 100 m, in a 25 m pool. Considering swimmers are typically required to complete a range of swim strokes (and modified strokes) over much longer distances, the ecological validity of these findings are limited. Therefore, the purpose of this study was to independently validate a swim training wearable sensor against video analysis, in a real training environment.

Methods

Subjects

Four male (21 ± 4 y, one national-level, three international-level) and six female (22 ± 3 y, one national-level, five international-level) swimmers participated in the study. Inclusion criteria required minimum five swim and two gym sessions per week, and currently competing at the national or international level. Written informed consent was obtained from all swimmers, and ethics approval was granted by the University of Technology Sydney Ethics Committee.

Design Methodology

The accuracy of a swim training monitoring device (TritonWear®, v1.2.3, 50 Hz, Ontario, Canada), containing a nine-axis inertial measurement unit with a tri-axial accelerometer, gyroscope, and magnetometer, was compared to video analysis.

The device was positioned under the swim cap, on top of each swimmer's occipital protuberance, in accordance with the manufacturer's recommendations.[5] Video footage was captured (Sony FS7 MII 4K 25 Hz, Minato, Tokyo) by placing the camera at a high vantage point, inside a building office on the side of the pool. Raw lap-by-lap footage for each session

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were analysed by the principle researcher using a performance analysis software package (Dartfish 10, 360-S, 2018, Switzerland).[3]

One of the most important limiting factors in the present study was the lack of timestamp in the device, meaning a running time between laps was not available for analysis. Therefore lap-by-lap comparison between the device and video analysis were not possible. A global measurement (i.e., total and mean) was subsequently used to examine the deviation of the device relative to video analysis. The swimming metrics analysed included total swim distance, total and mean stroke count, mean velocity, and stroke type.

Stroke types were coded into backstroke, breaststroke, butterfly, and freestyle. 'Drill' was included as an additional stroke identifier to denote activity completed during the warm up or active recovery (e.g., kick), when a swimmer did not use the same stroke type across a full lap, or when swimmers completed drills (e.g., 15 m efforts). Lap start was defined as when the swimmer pushed off the wall or dove into the pool, with lap end as the time of wall touch or tumble turn.

This study was conducted over 15 training days and included a total of 18 swim sessions (12 aerobic, 6 speed) in an Olympic-sized outdoor 50 m pool. Swimmers were separated by event classification to sprint (i.e., 50 to 200 m) or distance (i.e., ≥ 400 m). Training was prescribed within these classifications according to their regular swimming sessions.

Due to issues with video capture, only 15 of the 18 swimming sessions were included in the analysis process (10 aerobic, 5 speed). As a result of missed sessions by three swimmers, a total of 146 out of 150 individual swim sessions were available for comparison between the device and video.

Statistical Analysis

Validity data are presented as mean ± standard deviation (SD) for all variables. Absolute error was used to assess the overall difference of the device relative to video analysis, and standardised effect (i.e., mean difference/pooled SD) determined the size of this difference (i.e., 0.2 to 0.5 = 'small', 0.5 to 0.8 = 'medium', > 0.8 = 'large') with 95% confidence intervals.[8] Pearson's correlation coefficient examined the strength of the relationship between methods.

Fisher's Exact Test determined the percentage count frequencies across all stroke types, for both the device and video. Repeat reliability analysis was completed for one swimming session, across the 10 swimmers, with one month separating analyses. Log-transformed intraclass correlation coefficient (ICC) based on a multiple measurements, absolute agreement, 2-way mixed-effects model,[9] and typical error as a coefficient of variation (CV, %) with 95% confidence limits were calculated to determine intra-rater video analysis reliability for total swim distance, total and mean stroke count, mean velocity, and stroke type.

Results

High overall error was evident in the device across all swimming metrics (Table 1). The error led to consistent overestimation relative to the video analysis for total and mean stroke count, and mean velocity. Conversely, the device underestimated total swim distance relative to the video analysis.

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The device incorrectly detected total time spent in backstroke, breaststroke, butterfly, and freestyle by 51 ± 15% across all sessions ($p < 0.01$ for all strokes), with drill not identified (Figure 1). ICC intra-rater reliability was excellent between repeated measures for all swimming metrics (Table 2). The higher CV evident for backstroke and breaststroke are likely due to swimmers' lane positioning influencing the observer's capacity to differentiate between stroke cycles.

Discussion

This technical report demonstrates the wearable device assessed in the current study, does not accurately measure total swim distance, total and mean stroke count, mean velocity, or stroke type.

Across all sessions, the device incorrectly detected stroke type. The differences in stroke type detection could be explained through device placement. Previous research has demonstrated that wrist-based accelerometry has superior accuracy in detecting stroke type compared to devices worn on the head, or upper and lower back.[10] Specifically, freestyle and backstroke are best detected by wrist-worn devices due to the alternative mechanics allowing distinct differentiation of the strokes, whereas head-worn devices are better equipped to detect the body positioning and cyclical mechanics associated with breaststroke and butterfly, due to the exaggerated head movements associated with these strokes.[3] Therefore, device placement on the posterior head, as used in the present study, may have reduced the ability of the unit to accurately recognise stroke type. Currently, there remains no consensus regarding device placement,[4] which is likely to explain the variance in results in comparison to previous findings. The device's inability to identify and report time spent in drill activities is likely an additional contributing factor to the large discrepancies in stroke type detection and misclassification, relative to video analysis. Future studies must therefore assess which position, or combination of positions (e.g., wrist-based and head-worn), offers the most valid and reliable measure for stroke type identification.

The present results demonstrated consistent overestimation for total and mean stroke count from the device relative to video analysis. Indeed, the magnitude of the differences in these metrics were large, therefore limiting the practical use of these measures. These results are in contrast to previous research which reported the device was a valid measure of stroke count across 100 m for breaststroke and freestyle.[5] Consistent with stroke type identification, device placement and stroke misclassification may have also influenced stroke count recognition. For example, anecdotal observations noted the device would incorrectly code the stroke type if the swimmer had an exaggerated underwater kick. This stroke type misclassification may be a contributing factor to the difference in mean stroke count.

Accurate monitoring of swim distances and speeds are fundamental measures for swim training quantification.[11,12] The present findings revealed moderate and large errors of the device in total swim distance and mean velocity, respectively, relative to the video. Further improvement in device measurement properties is required before use in practice. Accordingly, it is recommended that future studies examine device firmware or algorithm upgrades as they become available, alongside assessment of other wearable devices for swimmers, to further measure the accuracy of the identified swimming metrics, in conjunction with additional variables (e.g., stroke rate).

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Practical Applications

- Swimmers, coaches, and sport scientists require precise data to monitor individual training responses. The use of the device in the current form to accurately monitor swimmer's training load is therefore limited until further developments in device algorithms or positioning occurs.

Conclusions

The inability of the device to accurately measure session distance, stroke count, and velocity, and to detect stroke type limit its application to monitor swimmers' training until further device improvements are available and independently validated. These findings are of importance to sport scientists and coaches who require accurate data to inform training prescription.

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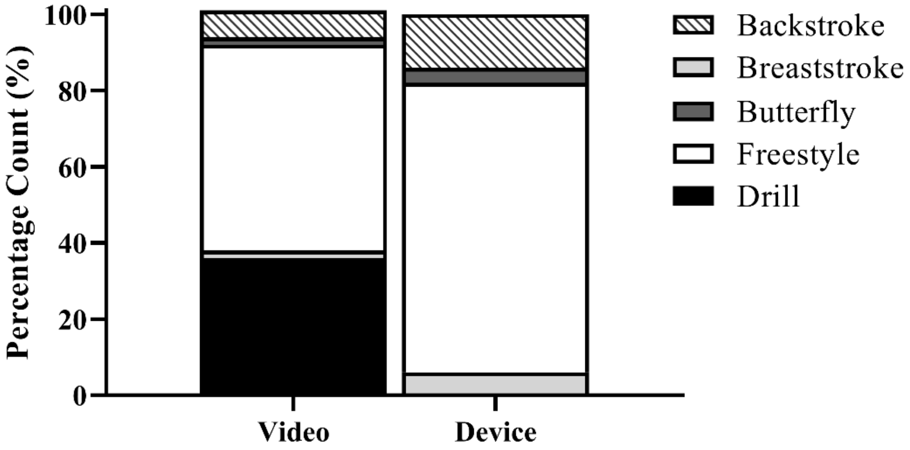

Figure 1. Percentage counts for total stroke type across all swimming sessions, as identified with the device and video analysis.

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Table 1. Validity of the device (TritonWear®) relative to video analysis. Data are presented as mean ± SD, Pearson's correlation, absolute error, and standardised effect (95% confidence intervals) for the swimming metrics across all 10 participant sessions (*n*=146).

Variable	Video	Device	Pearson's Correlation	Absolute Error	Standardised Effect
Total Swim Distance (km)	4.3 ± 0.9	3.7 ± 0.9	0.91	0.68 ± 0.39	0.70, medium (0.48-0.92)
Total Stroke Count (n)	2348 ± 619	2415 ± 708	0.93	174 ± 209	0.26, small (0.18-0.35)
Mean Stroke Count (n)	26 ± 5	33 ± 4	0.70	7 ± 3	1.26, large (0.86-1.66)
Mean Velocity (m/s)	1.2 ± 0.1	1.3 ± 0.1	0.24	0.11 ± .08	1.27, large (0.86-1.67)

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Table 2. Intra-rater reliability for video analysis. Data are presented as log-transformed intraclass correlation coefficient (ICC), and typical error as a coefficient of variation (CV, %) across all 10 participants within one swimming session, for total swim distance, total and mean stroke count, mean velocity, and stroke type identification (i.e., backstroke, breaststroke, butterfly, freestyle, and drill).

Variable	ICC	CV (%)
Total Swim Distance (km)	1.00	0.00
Total Stroke Count (n)	1.00	0.9
Mean Stroke Count (n)	1.00	0.9
Mean Velocity (m/s)	1.00	0.2
Backstroke (n)	0.96	12.9
Breaststroke (n)	0.97	11.1
Butterfly (n)	0.95	4.8
Freestyle (n)	0.99	1.6
Drill (n)	0.95	4.8