

1 **Original article**

2 **Title:** The validity of a head-worn inertial sensor for measurements of swimming performance.

3 **Titre:** Validité d'un capteur inertiel porté à la tête pour mesurer les performances en natation.

4

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17 **Running head:** "Validity of the inertial sensor for swimming"

18 **Key words:** Micro-technology; measurement error; water sports

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29 **Abstract**

30 The validity of the TritonWear® device to measure swimming performance was investigated,
31 with a pre-determined analytical goal of 6%. Twenty youth swimmers completed a 100 m swim
32 in a 25 m pool, swimming breaststroke or freestyle wearing the TritonWear® device, whilst
33 being filmed above and below water with three cameras. 95% Limits of Agreement (95% LoA)
34 and coefficient of variation (CV%) were used to calculate error. Systematic biases ($P < 0.05$)
35 were found between the two systems only for distance per stroke during breaststroke. Freestyle
36 metrics agreement ranged between 1.06 % and 10.40 % CV, except for distance per stroke (CV
37 = 14.64 %), and time underwater (CV = 18.15 %). Breaststroke metrics ranged between 0.95 %
38 and 13.74 % CV, except for time underwater (CV = 25.76 %). The smallest errors were found
39 for split-times, speed, stroke-count and stroke-rate, across both strokes (all $< 5\%$ CV). The
40 TritonWear® can be used for basic metrics of performance, such as split-time and speed but
41 the error of more complex measurements, such as time underwater or turn-times, renders them
42 unable to identify typical performance changes.

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44 **Résumé**

45 La validité du dispositif TritonWear® pour mesurer les performances en natation a été étudiée
46 avec un objectif analytique prédéterminé de 6%. Vingt jeunes nageurs ont réalisé une épreuve
47 de 100 m dans une piscine de 25 m, en brasse ou en nage libre en portant le dispositif
48 TritonWear®, tout en étant filmés au-dessus et en dessous de l'eau avec trois caméras. Les
49 limites de concordance à 95% (LoA à 95%) et le coefficient de variation (CV%) ont été utilisés
50 pour calculer l'erreur. Des biais systématiques ($p < 0,05$) ont été trouvés entre les deux systèmes
51 uniquement pour la distance parcourue par coup de bras en brasse. La concordance des
52 métriques en nage libre variait entre 1,06% et 10,40% du CV, sauf pour la distance par coup
53 de bras (CV = 14,64%) et le temps passé sous l'eau (CV = 18,15%). Les valeurs pour la brasse

54 variaient entre 0,95% et 13,74% du CV, sauf pour le temps passé sous l'eau (CV = 25,76%).
55 Les plus petites erreurs ont été trouvées pour les temps intermédiaires, la vitesse, le nombre de
56 coups de bras et la fréquence des coups de bras, pour les deux nages (tous <5% de CV). Le
57 TritonWear® peut être utilisé pour les mesures de performance de base, telles que le temps
58 intermédiaire et la vitesse, mais l'erreur sur des paramètres plus complexes, telles que la durée
59 d'immersion ou les temps de virage, ne permet pas d'identifier des modifications de ces
60 paramètres.

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79 **Introduction**

80 The margins of success and failure in competitive pool swimming are small, particularly in
81 sprint (< 400 m) events. For example, there are approximately 6% differences in velocity
82 between qualifiers and non-qualifiers of world championships (Takagi et al., 2004) and even
83 smaller differences (0.5 – 3 %) between 1st and 2nd place in 100 m Olympic finals
84 (<https://www.olympic.org/rio-2016/swimming>) or after training programme manipulation
85 (Mujika et al., 1995; Mujika et al., 2002). The 6% differences between qualifiers and non-
86 qualifiers (Takagi et al., 2004) is closely aligned with the training-induced performance
87 changes across key performance metrics. Therefore, a 6% change in performance provides the
88 most relevant differentiation of ability levels among competitive swimmers and is a change
89 that can be achieved owing to training. This threshold therefore represents a reasonable
90 ‘analytical goal’ (Atkinson & Nevill, 1998). Analytical goals are formulated to determine the
91 maximal level of measurement error that can be permitted by an investigator when using a
92 device to detect changes in performance. As such, the accuracy of testing equipment must be
93 sufficient to recognise anticipated changes in performance, which should be determined prior
94 to evaluation of its measurement error (analytical goals).

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96 Video- or sensor-based data devices are typically used to quantify swimming performance
97 (Beanland et al., 2014). Video analyses are considered to be the ‘gold standard’ method
98 (Ceseracciu et al., 2011) and are the most commonly used (Gourgoulis et al., 2008; Smith et
99 al., 2002). Despite this, video analysis techniques are complex and rely on the technical
100 expertise of the user (Knudson, 2007). Furthermore, their lower sampling rate 25-30 Hz is
101 likely to limit the accuracy of performance metrics during high-speed movements, such as
102 stroke rate or during turning manoeuvres. Wearable and water-proof microelectromechanical
103 systems (MEMS) provide a possible alternative to video analysis techniques (Callaway et al.,

104 2009; Dadashi et al., 2013; Ohgi et al., 2003). An example of this is the ‘TritonWear®’ device,
105 which claims to accurately measure speed and stroke efficiency metrics using a head-mounted
106 unit - the fitting of which causes less proprioceptive disruption than limb- or torso-worn devices
107 (Lecoutere & Puers, 2014).

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109 The TritonWear® technology measures a number of swimming performance metrics, such as
110 split-time, stroke count, speed, stroke rate, distance per stroke, turn-time and time underwater
111 (Lehary, 2015). Indeed, it is relevant to provide accurate measurements of these kinematic
112 variables, since success in swimming performance is largely explained by their combination
113 (Barbosa et al., 2010). Whilst others have investigated the validity of a global positioning
114 system-micro-technology (GPS) to quantify swimming performance metrics (Beanland et al.,
115 2014), these devices were not purpose-built for monitoring swimming performance. As such
116 limitations in the technology during water submersion, as well as raw sampling rate of GPS-
117 derived measurements (≤ 10 Hz) or the algorithmic treatment of raw MEMS signals on board
118 these units appeared to preclude their application. For example, stroke count was unreported
119 by Beanland et al. (2014) during freestyle swimming, owing to cumulative noise accrued by
120 the accelerometer during this stroke. Thus, the validity and reliability of a miniaturised
121 swimming-specific device intended for these key performance measurements is currently
122 unknown and could be used to replace more rudimentary chronometry, video methods or non-
123 specific micro-technology commonly used by swimming coaches.

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125 The aim of this study was to evaluate the validity of the TritonWear® device to measure
126 selected swimming performance metrics in comparison to a reference underwater video camera
127 system among competitive youth swimmers. For the current analysis, we adopted a
128 conservative *a-priori* analytical goal (see Atkinson & Nevill, 1998) that approximated the

129 typical changes observed in performance (split-time or speed) over a season among the current
130 or athletes in the literature of 6% (Takagi et al., 2004). The error (i.e. noise) between devices
131 for these variables should, therefore, permit the detection of signal changes of this magnitude.

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133 **Methods**

134 *Design and procedure*

135 Participants completed a 100 m swim in an outdoor 25 m swimming pool (4 x 25 m), swimming
136 either breaststroke or freestyle, wearing the TritonWear® device (The Triton Unit, firmware
137 version 1.1.2, 50 Hz, TritonWear Inc.®, Ontario, Canada), whilst being filmed above and
138 below water with fixed video cameras to evaluate validity. The two stroke-types were selected
139 as they were the two strokes used in competition by the current participants.

140

141 *Participants*

142 Ten male and ten female (total $n = 20$) competitive national swimmers (age 16 ± 3 years; stature
143 170 ± 15 cm; body mass 61.5 ± 14.7 kg) and their parent/guardian provided written informed
144 consent to participate in the study. All participants took part in all trials. Institutional ethical
145 approval was granted for this study.

146

147 *TritonWear® and Video Systems*

148 The components of the TritonWear® waterproof sensor unit include: a 9-axis inertial
149 measurement unit; a 3-axis digital accelerometer; a 3-axis digital gyroscope; a 3-axis digital
150 magnetometer; a micro-controller; a wireless module to transmit calculated metrics to the hub;
151 a clock to synchronise timing; and a lithium ion polymer battery with an internal battery
152 charging unit. The tracker reads oscillation data in three axes from the accelerometer and
153 gyroscope. The device measures 62 x 54 x 19 mm, weighs 51 g and is connected to the back

154 of the swimming goggle strap (Figure 1). The transmitted data were later analysed using the
155 manufacturer's software (TritonWear Insights, Ontario, Canada).

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157 ******Insert figure 1 here******

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160 Various metrics were analysed from the TritonWear® device. The start of each trial was
161 automated by the device as the internal gyroscope and accelerometer detect the swimmers
162 motion as they transition their head from a vertical to a horizontal position. As the swimmer
163 pushes off the wall, an increase in acceleration is detected by the accelerometer (sampling at
164 50 Hz), triggering an internal timer. The completion of a swim is determined by the following
165 characteristics in the signal from the sensors: an acceleration spike as the swimmer reaches the
166 wall, the transfer from horizontal to vertical head position, and finally, the decrease in
167 oscillatory signals being detected by the device.

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169 The TritonWear® device calculated all variables using the internal accelerometer and
170 gyroscope, which read and classify the oscillatory signals that are produced during swimming.
171 The push-off from the wall at the start of a swim was detected by the accelerometer, which
172 triggered a timer. Stroke type and stroke count were determined by the gyroscope, which
173 sensed the swimmers' angular velocities through three axes. The angular position for each axis
174 was determined using the numerical Euler method, which read the pitch, yaw and roll of the
175 swimmers' head as they moved through the water. Turn-time (s) was measured by the
176 gyroscope; the timer started at the downwards movement of the swimmer's head for freestyle
177 and the rotation movement in an open turn for breaststroke, and ended when the swimmer's
178 feet touched the wall, also capturing the end of a split. Time underwater (s) was calculated by

179 taking the time between the push-off from the wall (accelerometer), and the breakout event of
180 the head prior to the first stroke (gyroscope). Distance per stroke (m) was calculated by (length
181 of pool (m) – distance underwater (m)) / number of strokes. Speed (m/s) was determined by
182 calculating linear acceleration data and the change in time (acceleration x time) to determine
183 the average velocity of each swimmer for each length of the pool (m). Stroke rate (n/min) was
184 measured by subtracting the average time underwater from the average split-time, which is
185 then divided by the average number of stroke cycles in a length. For freestyle, one left hand
186 stroke and one right hand stroke equalled one stroke cycle. For breaststroke, each stroke is
187 counted as one stroke cycle. Once cessation of swimming was determined by the
188 accelerometer, the timer stopped and an overall time for the swim (split-time; s) was calculated.

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190 Three cameras were used, in combination, to track the performance of the swimmers. This
191 comprised two underwater cameras (WallMount Cam, 1080p, 30 frames/s, SwimPro®, RJB
192 Engineering, New South Wales, Australia) and one iPad 2 (1080p, 30 frames/s, Apple Inc.,
193 California, USA). Above water video was recorded using the iPad 2 and CoachesEye®
194 (TechSmith Corporation, Michigan, USA) analyses software. The underwater video cameras
195 were left running throughout the trials, whereas individual videos of swimmers were captured
196 using the iPad. The start and end of each trial was indicated by one investigator on the video,
197 so that it could be synchronized *post-hoc* with the TritonWear® recording analyses. One
198 experienced (> 5 years) investigator, with training and qualifications in performance analysis,
199 was responsible for video-based assessments. The operator had used the performance metrics
200 and the associated working definitions previously. Their intra-operator error for freestyle and
201 breaststroke video data ranged between 1.01 % and 5.89 % CV. Table 1 provides the criteria
202 that were used to ensure that each variable was objectively evaluated.

203

204 **Table 1.** Video analysis criteria.
205

Variable	Criteria
Split-time (s)	Clock started when the feet of the swimmer left the wall, to the time that the hand touched the wall on the final length. This figure was divided by four to give the average split-time.
Stroke count (<i>n</i>)	Freestyle: Each hand entry was recorded as one stroke, therefore one hand entry from each limb was counted as two strokes. Breaststroke: Each stroke was counted as one stroke.
Speed (m/s)	Average split-time was divided by the pool length (25 m).
Stroke rate (<i>n</i> /min)	The average time underwater was subtracted from the average split-time. This figure was then divided by the average number of stroke cycles in a length and expressed in minutes.
Distance per stroke (m/stroke)	The length of the pool - distance underwater / number of strokes identified.
Turn-time (s)	Freestyle: timing of the freestyle turn started when the head moved forwards and down, signalling the beginning of the swimmers turning action. The timer was stopped when the swimmer's feet hit the wall following the turn. Breaststroke: timing of the breaststroke turn started when the hands first touched the wall, signalling the beginning of the swimmers turning action. The timer was stopped when the swimmer's feet hit the wall prior to push-off.
Time underwater (s)	Timer started as the athlete's feet left the wall, timer stopped at first sight of the swimming cap above the surface of the water. Time underwater does not include turn-time.

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209 ***Statistical analyses***

210 Validity was assessed using a 95 % Limits of Agreement (95% LoA; (Atkinson and Nevill,
211 1998)) and coefficient of variation (CV%; (Hopkins, 2000). The current paper adopted an
212 analytical goal of 6% and based its interpretations on the CV technique. The 95% LoA was
213 provided for alternative interpretations among readers of the manuscript. Paired sampled *t*-tests
214 were used to calculate bias between the TritonWear® device and video-based system.
215 Statistical significance was set at $P < 0.05$ and adjusted for all dependant variables using a
216 Bonferroni correction.

217
 218 **Results**
 219

220 The data (mean \pm SD), CV% and 95% LoA for comparisons of the two devices are shown in
 221 Table 2. Comparison of the TritonWear® device against video analysis demonstrated no
 222 systematic biases ($P > 0.05$) for the freestyle stroke. For breaststroke, distance per stroke (t (9)
 223 = - 4.14, $P = 0.003$) showed systematic biases, while all other metrics did not ($P > 0.05$) (Table
 224 2).

Table 2. Validity of TritonWear® data against video analysis data ($n = 20$).

Validity Data	TritonWear (mean \pm s)	Video (mean \pm s)	95% LoA	CV (%)
<i>Freestyle</i>				
Split-time (s)	17.45 \pm 2.34	17.47 \pm 2.44	-0.021 \pm 0.51	1.06
Stroke count (n)	19.3 \pm 1.77	19.3 \pm 1.77	0.00 \pm 1.31	2.44
Speed (m/s)	1.41 \pm 0.19	1.45 \pm 0.17	-0.041 \pm 0.21	5.53
Stroke rate (n/min)	1.49 \pm 0.22	1.55 \pm 0.21	-0.065 \pm 0.13	3.01
Distance per stroke (m)	1.13 \pm 0.29	1.19 \pm 0.10	-0.065 \pm 0.47	14.64
Turn-time (s)	1.12 \pm 0.13	1.13 \pm 1.18	-0.003 \pm 0.32	10.40
Time underwater (s)	2.72 \pm 0.60	2.54 \pm 0.28	0.185 \pm 1.32	18.15
<i>Breaststroke</i>				
Split-time (s)	21.92 \pm 2.22	21.88 \pm 2.23	0.041 \pm 0.57	0.95
Stroke count (n)	10.70 \pm 2.06	10.8 \pm 1.93	-0.1 \pm 1.45	4.86
Speed (m/s)	1.14 \pm 0.14	1.15 \pm 0.11	-0.01 \pm 0.08	2.79
Stroke rate (n/min)	1.56 \pm 0.11	1.62 \pm 0.14	-0.06 \pm 0.17	3.77
Distance per stroke (m)	1.51 \pm 0.19	1.95 \pm 0.27	-0.44 \pm 0.66*	13.74
Turn-time (s)	1.56 \pm 0.23	1.36 \pm 0.13	0.19 \pm 0.52	12.91
Time underwater (s)	4.89 \pm 2.06	4.53 \pm 0.89	0.36 \pm 3.35	25.76

Note: LOA = 95% limits of agreement; CV = coefficient of variation. Significantly different ($P < 0.05$); *Statistical significance ($P < 0.05$).

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228 Freestyle metrics ranged between 1.06 % and 10.40 % CV, except for distance per stroke (CV
229 = 14.64 %), and time underwater (CV = 18.15 %). Freestyle 95 % LoA metrics ranged between
230 -0.065 ± 0.13 and 0.185 ± 1.32 . Breaststroke metrics ranged between 0.95 % and 13.74 % CV,
231 except for time underwater (CV = 25.76 %). Breaststroke 95 % LoA metrics ranged between -
232 0.01 ± 0.08 and 0.36 ± 3.35 (Table 2).

233

234 **Discussion**

235 The main finding of this study was that the TritonWear® device did not systematically differ
236 ($P > 0.05$) from the video-based system for most variables, besides distance per stroke in the
237 breaststroke. The CV values for split-time, speed, stroke-rate and stroke-count were all <5%
238 across both stroke types. As such, the error between the devices is smaller than the analytical
239 goal of 6%, providing a favourable signal-noise ratio, thus indicating that the Tritonwear®
240 device is valid for these measured variables. This means that an athlete could wear the device
241 for 100 m training or competition and receive a split-time, speed or stroke-based metric that
242 would agree with the reference system. However, based on the wide LoA and CV values for a
243 number of other variables (turn-time, time underwater and distance per stroke), the degree of
244 random error relative to the analytical goal of 6% questions their validity, leaving athletes
245 unable to detect performance changes using this device.

246

247 There is opportunity for both biological error (that of the human operator) and technical error
248 (that of the device) to affect the results of both systems used. The video-based system relies
249 upon certain factors, such as the quality of the synchronised videos, the ability of the human
250 eye to identify the start and end of a performance and the objectivity of the definitions used to
251 guide the human investigator. Given that the split-time definitions were identical between
252 devices and the investigators identified each variable in slow-motion (frame by frame), it is

253 most likely that the different technical specifications account for the small variations in basic
254 measurements of time and speed. For example, the different frame/sampling rates between
255 techniques (30 Hz frame/s vs. 50 Hz MEMS on the TritonWear®) mean that the investigator
256 might not be able to identify the exact time-point that the feet leave the wall, or reach the other
257 end, with the equal resolution whilst using the video system. An accumulation of these
258 discrepancies would lead to larger overall error across the 100 m swim duration. In addition to
259 this, there are a variety of on-board algorithms that correct for error in the TritonWear® device,
260 including advanced Kalman Filtering, that has capacity to correct for so-called ‘drifts’ based
261 on recent historical information, such as previous velocity. The accelerometry-derived
262 calculation of speed and iterative filtering processes, therefore, provide an advantage to the
263 TritonWear® relative to the video-based system, alongside its ease of application and real-time
264 feedback options for the swimmer.

265

266 The poorer agreement found for the more complex variables, such as time underwater and
267 distance per stroke can be explained by technical error. Naturally, these variables require
268 further computation and include input from a variety of sensors, at a higher frequency. For
269 example, time underwater was the most variable comparison and requires the consistent
270 recognition of two key events: i) push-off from the wall and ii) surfacing. These two events use
271 two separate miniaturised systems; the accelerometer and gyroscope, respectively. Recognition
272 of these discrete events presumably requires some achievement of a predicted threshold value,
273 as well as their temporal synchronisation. A scenario where the athlete pushed off the wall with
274 poor technique, or prematurely raised their head relative to their body, would be discordant
275 with the expected technical ‘model’ of performance. Based on the above, there are a variety of
276 both hardware and algorithmic degrees of freedom, which appear to have accumulated in the
277 TritonWear® device and resulted in measurement errors that are likely to preclude its

278 application with athletes in order to recognise changes in underwater time. This is important to
279 consider, as underwater time is an established predictor of performance in competitive pool
280 swimming (Vantorre et al., 2014) and, therefore, would be a useful tool for athletes to monitor
281 their progress during training. The video-based systems might be more labour-intensive but do
282 not suffer these same technical problems.

283

284 This study is not without limitations. For example, we were unable to access the raw signal of
285 the inertial sensors or the proprietary underlying algorithms, thus restricting our ability to fully
286 interrogate the signal processing or explore other methods of stroke analysis (see Dadashi et
287 al., 2015). This would be worthwhile, since the most erroneous measurements were those with
288 highest technical demand. Furthermore, the current analysis was constrained to 100 m
289 distances. Drift errors are more common while using IMUs across longer time periods.
290 However, the Kalman Filter used by the Tritonwear® was designed to correct for drift errors
291 and might partially remove this source of measurement noise, yet this requires further analysis
292 in future research. Finally, the video technique used was based on the performance of a single
293 operator and might be less repeatable among different users. The subjectivity of the technique
294 that is inevitably introduced when using human operators and poses a problem that can be
295 overcome by adopting automated measurement systems.

296

297 In conclusion, the TritonWear® device can be used by athletes or swimming practitioners for
298 basic metrics of performance, such as split-time, speed, stroke-rate and stroke-count. However,
299 the error for time underwater and distance per stroke in comparison to a reference system,
300 question the TritonWear® system's capacity to validly record these values.

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305 **Conflict of interest**

306 No potential conflict of interest is reported by the authors.

307

308

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311

312 **Author contributions**

313

314 All authors (MW,JB,JT,OJ,SP,LH) contributed to the conception and design of the study,
315 acquisition of data, analysis and interpretation of data, drafting the article, revising it critically
316 for important intellectual content and final approval of the version submitted.

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Figure



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Figure 1. Placement of TritonWear® device fitted directly inferior to the inion, on the occipital bone.