Journal of Sports Sciences, 2009; 1–8, i*First* article

Routledge
Taylor & Francis Group

Validity and reliability of kick count and rate in freestyle using inertial sensor technology

SACHA K. FULTON[1,2], DAVID B. PYNE[1], & BRENDAN BURKETT[2]

[1]*Department of Physiology, Australian Institute of Sport, Canberra, ACT and* [2]*School of Health and Sport Sciences, University of the Sunshine Coast, Maroochydore, Queensland, Australia*

(Accepted 27 April 2009)

Abstract

In freestyle swimming the arm action is routinely quantified by stroke count and rate, yet no method is currently available for quantifying kick. In this study, we assessed the validity and reliability of inertial sensor technology (gyroscope) to assess kick count and rate. Twelve Paralympic swimmers completed a 100-m freestyle-swimming time-trial and freestyle kicking-only time-trial three times each in a season. An algorithm was developed to detect the up and down beat of individual kicks from the gyroscope trace. For comparative purposes, underwater video analysis provided the criterion measure. The standard error of the estimate (validity) for kick count, expressed as a coefficient of variation, was 5.9% (90% confidence interval 5.5 to 6.4) for swimming, and 0.6% (0.5 to 0.6) for kicking-only trials. The mean bias for kick count was −1.7% (−2.4 to −1.1) for swimming, and −0.1% (−0.2 to −0.1) for kicking-only trials. Correlations between the sensor and video for kick count were 0.96 (0.95 to 0.97) for swimming, and 1.00 (1.00 to 1.00) for kicking-only trials. The typical error of the measurement (reliability) between trials was approximately 4% for kick count and rate. The inertial sensors and associated software used generated sufficient validity and reliability estimates to quantify moderate to large changes in kick count and rate in freestyle swimming.

Keywords: *Swimming, leg kick*

Introduction

The application of inertial sensor technology, systematically to track movement of the human body in sporting applications, is becoming well recognized in sports research. Inertial sensors are unobtrusive, lightweight, wireless, inexpensive, and commercially available, which makes them an attractive option for field-based research (Montoye, Kemper, Saris, & Washburn, 1996). Outside sport, inertial sensor technology is used to investigate posture and motion (VanAcht, Bongers, Lambert, & Verberne, 2007; Wong & Wong, 2008), ambulation (Cutti, Giovanardi, Rocchi, Davalli, & Sacchetti, 2008; Salarian, Russmann, Vingerhoets, Burkhard, & Aminian, 2007), and animal locomotion and behaviour (Pfau, Ferrari, Parsons, & Wilson, 2008; Venkatraman, Long, Pister, & Carmena, 2007). Other sports that have successfully implemented this technology include the martial arts karate and boxing (Ohgi, Mokuno, Yamagishi, & Miyaji, 1998) and running (Herren, Sparti, & Aminian, 1999).

Pilot studies a decade ago in swimming were one of the first sporting applications of inertial sensor technology. Analogue signals from the accelerometer trace of inertial sensors discriminated stroke cycles from a swimmer's forearm acceleration (Ohgi, Ichikawa, & Miyaji, 1999). Wireless inertial sensors worn on the wrist identified phases of the arm stroke, such as the down sweep, in sweep, out sweep, and recovery (Ichikawa, Ohgi, Miyaji, & Nomura, 2003; Ohgi, Ichikawa, Homma, & Miyaji, 2003). Swimmer fatigue has also been quantified by comparing the accelerometer traces obtained during intensive swimming sessions (Ohgi & Ichikawa, 2003). Uni-axial accelerometer inertial sensors have shown promise when strapped to a swimmer's back and have been used to detect swimming-specific characteristics such as lap times, dives and tumbling movements, stroke rate, stroke length, and intra-stroke acceleration. However, no published research has investigated the utility of inertial sensor technology to quantify kick count and kick rate. Information on kick count and kick rate patterns in swimmers

Correspondence: S. K. Fulton, AIS Residences, Leverrier Crescent, Bruce, ACT 2617, Australia. E-mail: sfulton@bigpound.net.au

ISSN 0264-0414 print/ISSN 1466-447X online © 2009 Taylor & Francis
DOI: 10.1080/02640410902998247

will enable coaches to ensure training programmes are conditioning the legs appropriately to meet kicking demands during competition.

The evaluation of sport-specific performance measures provides fundamental information to the coach, athlete, and sport scientist on an athlete's response to training (Smith, Norris, & Hogg, 2002). Practical and convenient methods of monitoring performance measures are especially important for sports such as swimming, where physiological and movement demands cannot be easily replicated in the laboratory (Robertson & Hunter, 2004). Until recently, discrimination of movement patterns in swimming was dependent on kinaesthetic information from the athlete or the lengthy process of joint digitization from video footage, making it difficult to evaluate a swimmer's stroke motion promptly after a trial. Visual information from an observer is often inaccurate given the water turbulence associated with swimming, where the legs especially are caught in a mass of white wash (Ohgi et al., 2003).

The aim of this study was to evaluate the application of inertial sensor technology to quantify kick count and kick rate in freestyle swimming. Because this method is comparatively new, the validity and reliability of these leg-kicking measures were quantified.

Methods

Participants

Twelve Paralympic swimmers (eight males aged 20.9 ± 4.2 years and four females aged 16.5 ± 2.1 years; mean $\pm$ s) participated in the study. The disabilities of the swimmers included cerebral palsy ($n = 5$), leg amputee ($n = 5$), and arm amputee ($n = 2$). The participants all had a freestyle world ranking in the top 20 for their class and were capable of performing a consistent flutter kick. Ethics approval was obtained before the start of the study from the Ethics Committee of the University of the Sunshine Coast and the Australian Institute of Sport.

Study design and procedures

Swimmers performed a maximal-effort 100-m freestyle-swimming time-trial and a 100-m freestyle kicking-only time-trial within 24 h of each other. These trials were performed on three occasions each (Trials 1 and 2, Trials 3 and 4, Trials 5 and 6), approximately 5 weeks apart. In every trial, swimmers wore an inertial sensor device taped to each available lower limb segment (thigh and shank). A total of 226 swimming trials and 217 kicking-only trials were included in the analysis for validity and reliability. The criterion measure for validity was determined from underwater video analysis. One-day reliability was reported between Trials 1 and 2 in each test session and five-week reliability was reported for Trials 1 and 3 between each test session.

On each test occasion there was typically 10–15 min active recovery between the 100-m freestyle-swimming and 100-m freestyle kicking-only time-trials. Swimmers started in the water and all trials were timed with a hand-held stopwatch. Swimmers were given equal verbal encouragement during each trial to ensure a maximal effort. Swimmers were instructed to swim to their normal race plan for the swimming trials and keep both hands on the kick board for the duration of the kicking-only trials. The inertial sensors were worn for each trial: one each on the left and right thigh and shank segment. Trans-femoral amputees ($n = 3$) wore two sensors on the unaffected side. Two swimmers wore a single sensor on the thigh of the affected side and one swimmer wore no sensor on the affected side as the amputation was high.

The inertial sensors (MiniTraqua^{TM}, version 5, Cooperative Research Centre for Microtechnology, Australian Institute of Sport) are housed in a waterproof plastic casing with external dimensions $5.2 \times 3.3 \times 1.1$ cm, mass of 20.7 g, and volume of 18.9 cm^3 (Figure 1). The device includes: a ± 2 g tri-axial accelerometer (Kionix; Model KMXM52, New York, USA); a single > 600 rad $\cdot$ s^{-1} angular-rate sensor (gyroscope); a 256-megabyte memory for data storage; USB interface for charging, calibrating, firmware upgrade, and downloading data; a

Figure 1. Inertial sensor package (MiniTraqua^{TM}) used to quantify kick count and kick rate. The image is presented to scale and is orientated as it appeared on the thigh and shank during testing.

rechargeable battery (approximately 3 h of operation); and a light-emitting diode screen for operational status indication. The internal electronic components of the device are commercially available. The packed unit was commissioned specifically for the Australian Institute of Sport and is not commercially available. The device was charged and calibrated via gold-plated conductors and a USB cradle. The recording system was configured for a 100-Hz sampling rate on all three accelerometer channels and the gyroscope channel. The gyroscope functionality was used to detect kick patterns given the absolute measure of angular velocity. Gyroscope calibration involved rotating the sensor from horizontal to vertical through the roll axis to calibrate for 90° of movement.

A software program (Logan, Version 21.9, Australian Institute of Sport) was developed to operate the inertial sensor, extract and process the data. A kick-detection algorithm was written specifically to identify a downwards trough in the 100-Hz gyroscope signal, filtered with a Butterworth filter with a cut-off frequency of 4 Hz (Schaumann & Van Valkenburg, 2001), using a 0.2-s sampling window. A complete kick was defined when the gyroscope signal started at 0 rad $\cdot$ s^{-1} (beginning of the down phase), crossed a subsequent 0 rad $\cdot$ s^{-1} (end of the down phase and beginning of the up phase), and returned to 0 rad $\cdot$ s^{-1} (end of the up phase). If the gyroscope trace did not return to zero following the beginning of the down phase, a kick was not registered. A typical image of the gyroscope trace depicting a complete kick is shown in Figure 2. A kick count was registered as the up and down beat of a single leg, and kick rate was derived as the number of kicks per unit time (kicks $\cdot$ min^{-1}).

All sensors were calibrated before use and verified immediately after use. The sensors were attached at the segmental centre of gravity of the thigh (trochanterion–tibiale laterale length) and shank (tibiale mediale–sphyrion tibiale length) and orientated vertically on the muscle belly. The accelerometer axes were aligned as follows: X axis parallel to the length of the limb segment (forwards/backwards movements) and Y axis perpendicular to the length of the limb segment (medio-lateral movements). The third axis (Z axis) calculated up/down movements. Unlike land-based sports, there are only certain locations on a swimmer's body where monitoring devices can be attached without causing major interference while swimming. In pilot trials, placement of the inertial sensors on the anterior or lateral sides of a swimmer's lower limb segments was uncomfortable or interfered with the streamlined position. Posterior placement on the lower limbs provided a clear gyroscope signal and did not inhibit kicking movements. The orientation ensured that the gyroscope functionality was used in its intended "roll" mode for kick detection and kept constant for all experimental trials. The sensors were placed in clear plastic zip lock bags for further waterproofing and attached using tape for comfort and security. No swimmer reported restriction of movement.

On completion of a swimming or kicking-only trial, data from each inertial sensor were downloaded via a USB interface. A cluster of vertical lines (kicks) on the gyroscope trace clearly identified each trial and each 25-m segment was manually identified to determine a count and rate. Raw data were exported to a spreadsheet to calculate mean kick rate for each segment. Underwater video footage was manually inspected to validate the sensor's kick count. The same researcher completed the video inspection, download and data compilation process for all trials. The first and last kick of each lap was difficult to identify, even with inspection of video footage. To estimate the magnitude of the first kick and last kick error we conducted a short simulation. A probability, set at 33.3%, estimated each setting (i.e. the sensor under-counting, over-counting or counting correctly the first and last kick of each lap) by calculating the typical error of a large number of laps (over 1200).

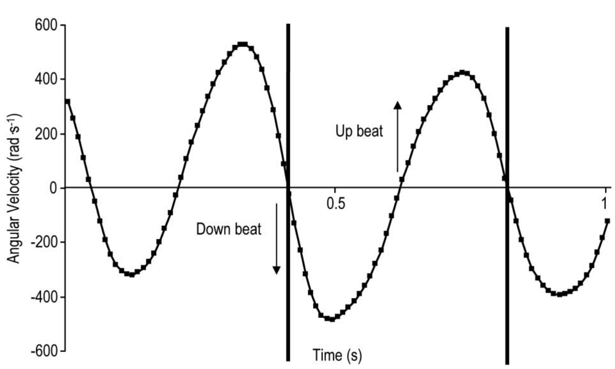

Figure 2. A typical gyroscope trace for one second of data capture from the inertial sensor. A single complete kick, indicated by the vertical black lines, consists of a combined down beat and up beat starting from 0 rad $\cdot$ s^{-1} and ending when the limb segment has returned to 0 rad $\cdot$ s^{-1}.

Statistical analysis

Kick-count validity was established between the inertial sensor and kicks counted manually from underwater video footage. The standard error of the estimate was reported in raw and standardized (coefficient of variation) units. The mean bias was reported in raw units and as a percentage. The precision of estimates was indicated with 90% confidence intervals. Pearson's correlation coefficient was used to assess the relationship between the inertial sensor and underwater video analysis for swimming and kicking-only trials. The magnitude of correlation was interpreted as: trivial <0.10, small 0.10–0.29, moderate 0.3–0.5, and large >0.5. A relationship was considered unclear if the 90% confidence interval overlapped both the substantial positive and negative threshold (r-value of ± 0.1) (Hopkins, 2004).

One-day and five-week reliability for kick count and kick rate was reported as the typical error of the measurement and expressed in raw and standardized (coefficient of variation) units with 90% confidence intervals. Intra-class correlation coefficients (ICC) were calculated to interpret the reliability of the repeated measures. An ICC less than 0.40 represented poor reliability, 0.40–0.70 fair reliability, 0.71–0.90 good reliability, and >0.90 represented excellent reliability (Fleiss, 1986). To determine the signal- (the magnitude of a worthwhile change or difference in kick characteristics) -to-noise (the typical error or test–retest reliability) ratio, the smallest worthwhile effect was calculated as 0.2 (the default value for the smallest worthwhile effect) of the between-swimmer variability in accordance with existing methods (Hopkins, 2000). To reduce the likelihood of heteroscedascity (non-uniformity of error), the data were log-transformed before analysis (Paton & Hopkins, 2005). Log-transformed data were back-transformed to obtain changes and differences as a percentage (Stewart & Hopkins, 2000). To interpret the observed magnitude of differences of coefficients of variation, we used a threshold ratio of 1.15 (Hopkins & Hewson, 2001).

Results

The standard error of the estimate between the inertial sensor and underwater video footage for kick count is shown in Table I. The coefficient of variation (CV) between the sensor and video footage was 5.9% (90% confidence interval 5.5 to 6.4) for swimming trials and 0.6% (0.5 to 0.6) for kicking-only trials. In raw units the standard error of the estimate was 6.4 (5.9 to 6.9) and 1.4 (1.3 to 1.5) kicks for the swimming and kicking-only trials respectively. The estimate of kick count for swimming trials was substantially more variable than for kicking-only trials (ratio of CV 9.8, 8.8 to 11.0). Within swimming trials, kick count of the right leg was substantially more variable than that of the left leg (ratio of CV 3.6, 3.1 to 4.2). In the kicking-only trials, kick count of the left leg was substantially more variable than that of the right leg (ratio of CV 2.3, 2.0 to 2.7). In the swimming (ratio of CV 1.2, 1.0 to 1.4) and kicking-only (ratio of CV 4.0, 3.4 to 4.7) trials, kick count for the shank was substantially more variable than for the thigh. From computer simulation, an additional typical error of approximately 1.1% was calculated for every 100 kicks.

The mean bias of the inertial sensor for detecting kick count in freestyle swimming and kicking-only trials for each individual swimmer is shown in Table II. The inertial sensor typically recorded a lower kick count than the video with a mean bias of -1.7% (90% confidence interval -2.4 to -1.1) for swimming trials and -0.1% (-0.2 to -0.1) for kicking-only trials. In raw units, the inertial sensor typically recorded -2.0 (-2.7 to -1.3) and -0.3 (-0.5 to -0.2) kicks per 100 m less than the underwater video footage for swimming and kicking-only trials respectively. In freestyle-swimming trials, the bias was -7.2% (-12.5 to -1.6) for swimmer 2 and -7.2% (-11.0 to -3.1) for swimmer 8, where the inertial sensor underestimated kick count by -7.3 (-12.6 to -2.0) and -9.3 (-14.6 to -4.0) kicks per 100 m respectively. The swimmers were of different disabilities and closer inspection of their kicking patterns during swimming trials from the underwater video footage could not identify any definitive explanation for the skewed results. The Pearson correlation coefficient between the inertial sensor and underwater video measures are shown in Figure 3.

One-day and five-week estimates of the reliability of kick count and kick rate for swimming and kicking-only trials are shown in Table III. The reliability of quantifying kick count (ratio of CV 1.8, 1.6 to 2.2) and kick rate (ratio of CV 1.3, 1.1 to 1.5) from day to day was substantially lower for

Table I. The standard error of the estimate (SEE) expressed in raw units and as a coefficient of variation (CV) with 90% confidence limits (90% CL) for kick count validity ($n = 12$).

	Swimming trials		Kicking-only trials	
Side/segment	SEE (raw units)	CV (%)	SEE (raw units)	CV (%)
Left side	2.5 (2.2 to 2.8)	2.1 (1.9 to 2.3)	1.7 (1.5 to 1.9)	0.7 (0.6 to 0.8)
Right side	8.1 (7.2 to 9.2)	7.5 (6.7 to 8.5)	0.8 (0.7 to 0.9)	0.3 (0.3 to 0.4)
Thigh segment	4.7 (4.2 to 5.3)	5.3 (4.8 to 6.0)	0.4 (0.4 to 0.5)	0.2 (0.1 to 0.2)
Shank segment	7.5 (6.8 to 8.4)	6.4 (5.7 to 7.2)	1.9 (1.7 to 2.1)	0.8 (0.7 to 0.9)
Mean	6.4 (5.9 to 6.9)	5.9 (5.5 to 6.4)	1.4 (1.3 to 1.5)	0.6 (0.5 to 0.6)

Table II. Mean bias of inertial sensor for kick count detection in freestyle swimming and kicking-only trials, expressed in raw units and as a percentage with 90% confidence limits (90% CL), by individual swimmer ($n = 12$).

	Swimming		Kicking only	
Swimmer	Raw bias	% Bias	Raw bias	% Bias
Swimmer 1	-0.1 ± 0.1	-0.1 ± 0.1	-0.1 ± 0.2	-0.1 ± 0.1
Swimmer 2	-7.3 ± 5.3	-7.2 ± 5.4	-0.2 ± 0.3	-0.1 ± 0.1
Swimmer 3	-0.9 ± 1.1	-1.0 ± 1.2	-0.1 ± 0.2	-0.1 ± 0.1
Swimmer 4	-0.7 ± 2.2	-0.8 ± 1.1	-0.0 ± 0.0	-0.0 ± 0.0
Swimmer 5	-1.1 ± 0.7	-1.1 ± 0.7	-0.3 ± 0.3	-0.2 ± 0.2
Swimmer 6	-1.8 ± 1.6	-1.5 ± 1.3	-0.1 ± 0.1	-0.0 ± 0.1
Swimmer 7	-0.1 ± 0.1	-0.1 ± 0.1	-0.1 ± 0.1	-0.0 ± 0.0
Swimmer 8	-9.3 ± 5.3	-7.2 ± 4.0	-0.5 ± 0.4	-0.2 ± 0.2
Swimmer 9	-1.3 ± 1.3	-1.0 ± 1.0	-1.7 ± 1.5	-0.7 ± 0.6
Swimmer 10	-0.0 ± 0.0	-0.0 ± 0.0	-0.0 ± 0.0	-0.0 ± 0.0
Swimmer 11	-0.2 ± 0.4	-0.2 ± 1.0	-0.3 ± 0.4	-0.1 ± 0.3
Swimmer 12	-0.1 ± 0.1	-0.0 ± 0.1	-0.2 ± 0.1	-0.1 ± 0.1
Mean	-2.0 ± 0.7	-1.7 ± 0.7	-0.3 ± 0.2	-0.1 ± 0.1

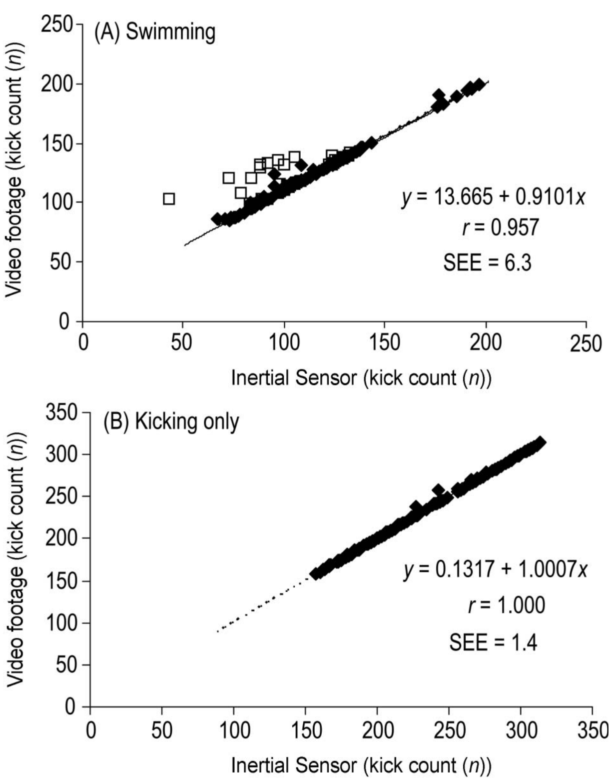

Figure 3. Scatter plot showing the relationship between the inertial sensor (x axis) and underwater video methods (y axis) for quantifying kick count in the swimming (A) and kicking-only (B) trials. The open symbols show two swimmers whose kick count during the swimming trials skewed the results.
[a]One-day reliability was reported between two trials at each testing session. [b]Five-week reliability was reported for two trials between each testing session.

swimming than kicking-only trials; no substantial differences were observed for five-week reliability. Trials five weeks apart were slightly less reliable than trials one day apart for swimming for kick count (ratio of CV 1.2, 1.0 to 1.4); there was no substantial difference for kick rate. For kicking-only trials, day-to-day reliability was substantially less than trials five weeks apart for kick count (ratio of CV 1.2, 1.0 to 1.4) and kick rate (ratio of CV 1.4, 1.2 to 1.6).

In the swimming trials, kick count on the right was slightly less reliable than that on the left (ratio of CV 2.5, 1.7 to 2.7); there was no substantial difference for kick rate. The thigh was less reliable than the shank for kick count (ratio of CV 1.4, 1.1 to 1.7); there was no substantial difference for kick rate. The correlation between sensor data and video analysis for kick count rate over one day and five weeks ranged from 0.90 to 0.95. The magnitude of the smallest worthwhile effect for one day reliability was 3.5 kicks for kick count and 2.4 kicks $\cdot$ min^{-1} for kick rate per 100 m. Magnitudes for five-week reliability were 3.3 kicks for kick count and 2.5 kicks $\cdot$ min^{-1} for kick rate per 100 m.

In the kicking-only trials, there were no substantial differences in kick count or kick rate between left and right or between the thigh and shank. The correlation between sensor data and video analysis for kick-count rate over one day and five weeks ranged from 0.86 to 0.98. The magnitude of the smallest worthwhile effect for one-day reliability was 4.1 kicks for kick count and 2.4 kicks $\cdot$ min^{-1} for kick rate per 100 m. Magnitudes for five-week reliability were 4.1 kicks for kick count and 2.5 kicks $\cdot$ min^{-1} for kick rate per 100 m.

Discussion

In this study, we assessed kick count and kick rate in freestyle swimming using inertial sensor technology, and found that the new method produced valid and reliable measures that could quantify moderate-to-large changes. Kicking movements that are otherwise difficult to detect can now be identified with this

Table III. The standard error of the measurement (SEM) expressed in raw units and as a coefficient of variation (CV) with 90% confidence limits (90% CL) for reliability ($n = 12$).

	Swimming trials		Kicking-only trials	
Kick variable	SEM (raw units)	CV (%)	SEM (raw units)	CV (%)
Count (one day)	5.7 (5.1 to 6.4)	4.6 (4.0 to 5.6)	7.4 (6.6 to 8.3)	3.0 (2.7 to 3.4)
Count (five weeks)	10.2 (9.3 to 11.3)	3.9 (3.5 to 4.5)	9.0 (8.1 to 10.1)	3.8 (3.4 to 4.2)
Rate (one day)	4.2 (3.8 to 4.8)	3.5 (3.1 to 3.9)	3.8 (3.4 to 4.3)	2.8 (2.4 to 3.3)
Rate (five weeks)	4.8 (4.4 to 5.3)	3.9 (3.6 to 4.4)	4.9 (4.5 to 5.5)	3.9 (3.5 to 4.3)

technology. In this study, the standard error of the estimate for kick count validity was substantially greater in swimming trials, approximately six kicks per 100 m, than kicking-only trials, approximately one kick per 100 m. This is presumably attributable to the more pronounced biomechanics of the kicking-only action that elicits more clearly defined troughs for kick detection. Variation in the first and last kicks of a lap had little effect on the overall estimates of kick count and rate, although two individual swimmers did markedly inflate the standard error of the estimate for kick count validity. Large correlations between the inertial sensor and underwater video confirm the suitability of kick count detection for swimming and kicking-only trials.

In the current study, the inertial sensor detected kicks from a series of troughs in a gyroscope trace. The sensor slightly underestimated kick count for swimming trials with a mean bias of -1.7% and for kicking only-trials this reduced to only -0.1%. Kick count tended to be underestimated by the inertial sensor by no more than two kicks for every 100-m trial swum. Other research using wrist-mounted inertial sensor technology applications in swimming reported a mean bias of 0.0% to 2.0% for accelerometer axes for the discrimination of freestyle and breaststroke strokes (Ohgi et al., 1999). Similarly, hip-mounted accelerometer applications in physical activity research have reported a mean bias of 0.8% to 1.1% in detecting walking steps at a range of speeds (Le Masurier & Tudor-Locke, 2003). A mean bias of 1–2% in kicking characteristics is favourable given a preliminary report that for arm-stroke count and stroke-rate detection in freestyle swimming using triaxial acclerometry, the mean bias was approximately 5–10% (M. Anderson, unpublished data). The reason for the greater bias in arm-stroke than leg-kick detection in the current study is the movement pattern of the kick. The action is confined to a single plane, which makes the inertial detection simpler. Substantially greater errors were calculated in the stroke detection at faster swimming speeds and, similar to the current study, high errors were specific and limited to a few individual swimmers (M. Anderson, unpublished data). The kick-count variation of only 1–2% detected by this technology and software suggests that the new method is an effective measure of kick count.

The evaluation of semi-automated kick count and kick-rate detection using inertial sensor technology yielded small differences between swimming and kicking-only trials, and between the one-day and five-week time frames. Coaches and scientists can use this technology to identify changes in kick count and rate patterns between training sessions and for seasonal changes between major competitions. Semi-automated inertial sensor technology orientated on the lower limbs for kick count and kick-rate detection also yielded small differences between the left and right side and between the thigh and shank segment. There is no definitive explanation to account for these differences, as all swimmers were able to kick consistently. Future studies and test sessions should consider placement on a single lower limb segment. The shank of a swimmer's dominant leg, more applicable for Paralympic swimmers, should be the location of choice. In terms of the signal-to-noise ratio, the sensor is best suited for identifying moderate-to-large changes in kick patterns. The inherent noise in sensor output makes it problematic to identify small changes or differences in kicking. Improvements in the technology and software, coupled with duplicate measures or repeat trials, would increase the likelihood of detecting small changes in kick-count and kick-rate patterns within and between training seasons.

Researchers have orientated inertial sensors on various parts of the body to identify movement patterns. To monitor physical activity, sensors have been worn in the hip region held against the body in velcro pouches secured with a waist strap (Anderson, Hagstromer, & Yngve, 2005; Le Masurier & Tudor-Locke, 2003; Nichols, Morgan, Chabot, Sallis, & Calfas, 2000). In swimming and martial arts, sensors have been attached to the wrist by a wrist band (Ichikawa, Ohgi, & Miyaji, 1999; Ichikawa et al., 2003; Ohgi & Ichikawa, 2003; Ohgi et al., 1998, 1999, 2003; Ohgi, Yasumura, Ichikawa, & Miyaji, 2000). The inertial sensor devices used in this study were orientated on a swimmer's lower limbs and attached without discomfort or restriction of movement. Future studies could investigate modifying racing leggings to incorporate this type of sensor device and eliminate the attachment process. Inertial sensor technology could be further developed to quantify multi-segmental limb displacement, which could be used by coaches and swimmers to optimize kicking range of movement. Quantifying angular-velocity and acceleration patterns and the propulsive role of the legs would provide useful information for researchers and ultimately coaches and athletes.

The inertial sensor technology and associated software used in this study is sufficiently valid and reliable to quantify moderate-to-large changes in kick count and kick rate in freestyle swimming. The technology can be used by coaches and researchers interested in quantifying kick patterns in swimming to guide training regimes and for biomechanical and performance enhancement applications. In a single timed effort, coaches and researches can anticipate strong agreement between the sensor and video analysis for detecting kick count in freestyle swimming. Future studies might investigate the application of this system to the other competitive swimming strokes. A limitation of the current system is the single angular rate sensor gyroscope, which is not capable of detecting a change in kicking technique. Refinements to the current system are needed to automate the kick detection process, reduce associated measurement error, and increase reproducibility when reporting small changes in kicking patterns.

References

Anderson, C. B., Hagstromer, M., & Yngve, A. (2005). Validation of the PDPAR as an adolescent diary: Effect of accelerometer cut points. *Medicine and Science in Sports and Exercise*, *37*, 1224–1230.

Cutti, A. G., Giovanardi, A., Rocchi, L., Davalli, A., & Sacchetti, R. (2008). Ambulatory measurement of shoulder and elbow kinematics through inertial and magnetic sensors. *Medical and Biological Engineering and Computing*, *46*, 169–178.

Fleiss, J. L. (1986). *The design and analysis of clinical experiments.* New York: Wiley.

Herren, R., Sparti, A., & Aminian, K. (1999). The prediction of speed and incline in outdoor running in humans using accelerometry. *Medicine and Science in Sports and Exercise*, *31*, 1053–1059.

Hopkins, W. G. (2000). Measures of reliability in sports medicine and science. *Sports Medicine*, *30*, 1–15.

Hopkins, W. G. (2004). How to interpret changes in an athletic performance test. *Sportscience*, *8*, 1–7.

Hopkins, W. G., & Hewson, D. J. (2001). Variability of competitive performance of distance runners. *Medicine and Science in Sports and Exercise*, *33*, 1588–1592.

Ichikawa, H., Ohgi, Y., & Miyaji, C. (1999). Analysis of stroke of the freestyle swimming using accelerometer. In K. L. Keskinen, P. V. Komi, & A. P. Hollander (Eds.), *Biomechanics and medicine in swimming VIII* (pp. 159–165). Jyväskylä, Finland: Gummerus Printing.

Ichikawa, H., Ohgi, Y., Miyaji, C., & Nomura, T. (2003). Estimation of arm motion in front crawl swimming using accelerometer. In J. C. Chatard (Ed.), *Biomechanics and medicine in swimming IX* (pp. 133–138). Saint-Étienne, France: Publications de l'Université de Saint-Étienne.

Le Masurier, G. C., & Tudor-Locke, C. (2003). Comparison of pedometer and accelerometer accuracy under controlled conditions. *Medicine and Science in Sports and Exercise*, *35*, 867–871.

Montoye, H. J., Kemper, H. C., Saris, W. H., & Washburn, R. A. (1996). *Measuring physical activity and energy expenditure.* Champaign, IL: Human Kinetics.

Nichols, J. F., Morgan, C. G., Chabot, L. E., Sallis, J. F., & Calfas, K. J. (2000). Assessment of physical activity with the Computer Science and Applications, Inc., accelerometer: Laboratory versus field validation. *Research Quarterly for Exercise and Sport*, *71*, 36–43.

Ohgi, Y., & Ichikawa, H. (2003). Fatigue evaluation by using micro-based acceleration data logger for swimming research. In J. Chatard (Ed.), *Biomechanics and medicine in swimming IX* (pp. 463–468). Saint-Étienne, France: Publications de l'Université de Saint-Étienne.

Ohgi, Y., Ichikawa, H., Homma, M., & Miyaji, C. (2003). Stroke phase discrimination in breaststroke swimming using a tri-axial acceleration sensor device. *Sports Engineering*, *6*, 119–123.

Ohgi, Y., Ichikawa, H., & Miyaji, C. (1999). Characteristics of the forearm acceleration in swimming. In K. L. Keskinen, P. V. Komi, & A. P. Hollander (Eds.), *Biomechanics and medicine in swimming VIII* (pp. 77–82). Jyväskylä, Finland: Gummerus Printing.

Ohgi, Y., Mokuno, T., Yamagishi, M., & Miyaji, C. (1998). A methodology for analysing human movement patterns and performance using acceleration time series. In S. J. Haake (Ed.), *The engineering of sport* (pp. 465–472). Oxford: Blackwell Science.

Ohgi, Y., Yasumura, M., Ichikawa, H., & Miyaji, C. (2000). Analysis of stroke technique using acceleration sensor IC in freestyle swimming. In A. J. Subic & S. J. Haake (Eds.), *The engineering of sport: Research, development and innovation* (pp. 503–511). Oxford: Blackwell Science.

Paton, C. D., & Hopkins, W. G. (2005). Competitive performance of elite Olympic-distance triathletes: Reliability and smallest worthwhile enhancement. *Sportscience*, *9*, 1–5.

Pfau, T., Ferrari, M., Parsons, K., & Wilson, A. (2008). A hidden Markov model-based stride segmentation technique applied to equine inertial sensor trunk movement data. *Journal of Biomechanics*, *41*, 216–220.

Robertson, E., & Hunter, A. (2004). The physiological demands of simulated swimming on a dry-land swimming ergometer compared to swimming in a 50m pool. Paper presented at the 9th Annual Congress of the European College of Sports Science, Clermont-Ferrand, France.

Salarian, A., Russmann, H., Vingerhoets, F. J., Burkhard, P. R., & Aminian, K. (2007). Ambulatory monitoring of physical activities in patients with Parkinson's disease. *IEEE Transactions on Biomedical Engineering*, *54*, 2296–2299.

Schaumann, R., & Van Valkenburg, M. E. (2001). *Design of analog filters.* New York: Oxford University Press.

Smith, D. J., Norris, S. R., & Hogg, J. M. (2002). Performance evaluation of swimmers: Scientific tools. *Sports Medicine*, *32*, 539–554.

Stewart, A. M., & Hopkins, W. G. (2000). Seasonal training and performance of competitive swimmers. *Journal of Sports Sciences*, *18*, 873–884.

VanAcht, V., Bongers, E., Lambert, N., & Verberne, R. (2007). Miniature wireless inertial sensor for measuring human motions. Paper presented at the *29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Lyon, France.

Venkatraman, S., Long, J. D., Pister, K. S., & Carmena, J. M. (2007). Wireless inertial sensors for monitoring animal behaviour. Paper presented at the *29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Lyon, France.

Wong, W. Y., & Wong, M. S. (2008). Trunk posture monitoring with inertial sensors. *European Spine Journal*, *17*, 743–753.