MEASURING INSTANTANEOUS VELOCITY IN FOUR SWIM STROKES USING AN AUTOMATIC VIDEO-BASED SYSTEM: A COMPARISON STUDY

Michelle Scott[1], Nathan Elsworthy[1], Marc Elipot[2], Victoria Brackley[3] and Crystal O. Kean[1]
[1]School of Health, Medical and Applied Sciences, Central Queensland University, QLD, Australia
[2] Swimming Insight, Swimming Australia, Brisbane, Australia
[3]Victorian Institute of Sport, VIC, Australia

This study compared instantaneous swimming velocity from an automated video-based system to a tethered speedometer. Twenty-two state- and national-level swimmers (7 M, 15 F; 14.5 ± 2.5 yrs) swam 25 m of each stroke at maximal intensity. Bland-Altman plots showed good agreement between systems for backstroke and freestyle but poorer agreement for butterfly and breaststroke. The RMS error was also lower in backstroke and freestyle compared to butterfly and breaststroke. The differences in systems may be explained by the different body segments tracked by each system (head vs hips) and with differences being more apparent during butterfly and breaststroke due to the wave-like motion of these strokes. While the automated video-based system is suitable for measuring instantaneous swimming velocity, coaches, sports scientists, and swimmers should be aware of larger discrepancies between systems when assessing butterfly and breaststroke.

KEYWORDS: concurrent validity, performance analysis, speedometer

INTRODUCTION: Intra- and inter-cyclic velocity variations derived from instantaneous swimming velocity are key to assessing the net effect of propulsive and drag forces acting on a swimmer (Barbosa et al., 2019; Elipot et al., 2019). Therefore, it is important that instantaneous swimming velocity is accurately measured in training and competition to enable coaches, sports scientists, and swimmers to evaluate and improve performance.

Instantaneous swimming velocity has traditionally been measured using tethered speedometers, which have been shown to be valid in the four swimming strokes at maximal intensity (Feitosa et al., 2013a, 2013b). However, velocity measurement is restricted to one lap and training. While video-based systems are commonly used in competition and training, traditional video analysis involves time-consuming manual digitisation, which often leads to delayed feedback to coaches and swimmers (Mooney et al., 2015). During the last decade, inertial measurement units (IMUs) have emerged as a valid alternative to measure instantaneous swimming velocity across multiple laps (Stamm et al., 2013; Mooney et al., 2016; Clément et al., 2021). However, signal drift leads to rapid degradation of velocity estimation over time (Mooney et al., 2016). Given the limitations of tethered speedometers, traditional video analysis, and IMUs, automated video-based systems have been developed (Hall et al., 2021; Benarab et al., 2017; Haner et al., 2015). These automated video-based systems use deep learning algorithms (i.e., computer vision technology) to automatically detect a swimmer in near real processing time. While these systems can be limited by the quality and quantity of videos in the training sets; such systems have been shown to accurately detect a swimmer's head position and subsequently calculate instantaneous swimming velocity (Elipot et al., 2019; Hall et al., 2021; Benarab et al., 2017; Haner et al., 2015).

Given many systems exist to measure instantaneous velocity, it is important to know the agreement between such systems. Therefore, our study aimed to examine the agreement of instantaneous swimming velocity measures in the four swimming strokes between a tethered system and an automated video-based system that uses the DeepDASH approach (Elipot et al., 2019; Hall et al., 2021).

METHODS: Twenty-two competitive swimmers (7 male, 15 female, age: 14.5 ± 2.5 years, height: 168.0 ± 8.9 cm, mass: 63.3 ± 10.5 kg) were recruited from a local swimming club.

Swimmers were included if they were aged 12 years or older and had competed at an Australian State or National competition in the current or previous swimming season.
Each participant performed a warm-up, and two 25 m familiarisation trials, followed by one maximal effort 25m trial of each swim stroke. Maximal effort trials were performed in individual medley order with approximately 2 min rest between trials. To minimise the underwater distance at the start of each trial, participants were instructed to perform a gentle push start off the wall and, upon surfacing, swim the remainder of the 25 m at maximal effort.
Data was collected during each maximal effort trial using 1) a tethered speedometer with custom measurement software (RX Swim Capture App V21.10.30.0, AMR Sport, Parkwood, Australia) and 2) a single, fixed, ultra-high definition camera with a wide-angle lens Canon EF-S 10-22 mm, Canon Australia Proprietary Limited, Sydney, Australia). The tethered speedometer and associated laptop computer were positioned on the pool deck adjacent to the lane starting block. The nylon line of the tethered speedometer was fastened to a Velcro belt and placed at the central point of the lumbar region of the swimmer. The camera was positioned at the highest level of the grandstand adjacent to the pool, which allowed the entire 25 m of each trial to be captured in the field of view and videos of each trial were recorded at 50 Hz. Two white light-emitting diode (LED) lights connected to the tethered speedometer, were positioned in the field of view of the camera and allowed for post-process synchronising of the data from the two systems.
Tethered speedometer data was exported to a .csv file using post-processing software (MotionStudio SwordFish Edition V21.2.27.0, AMR Sport, Parkwood, Australia. Thereafter, the data were resampled to 50 Hz in Matlab® (R2022a, The MathWorks, Inc., Natick, Massachusetts, United States). Residual analyses were performed to determine the most appropriate cut-off filtering frequency (Winter, 2009). The optimal cut-off frequency for each trail was determined and the average cut-off frequency for each stroke was subsequently calculated. Consequently, velocity data from the tethered speedometer was filtered using a third-order Butterworth filter with cut-off frequencies of 9 Hz for backstroke and 10 Hz for butterfly, breaststroke, and freestyle.
The video data was post-processed using proprietary software as described in Hall et al. (2021). In short, the video frame in which the LED lights were activated was initially identified and set the time as 0 s for each trial. The two-dimensional image-space of the video recordings were then calibrated to real-world coordinates (Hall et al., 2021). The DeepDASH algorithm and HISORT algorithm were applied to automatically detect and track the swimmers as outlined in Elipot et al. (2019) and Hall et al. (2021). Instantaneous swimming velocity in the horizontal direction (i.e., along the swimming lane) (Hall et al., 2021) were determined and filtered using a third-order Butterworth filter with cut-off frequencies of 7 Hz for backstroke and freestyle, 8 Hz for butterfly, and 9 Hz for breaststroke. These cut-off frequencies were determined based on residual analysis on 20 random trials from a larger database and represent the average cut-off frequency for each stroke.
Processed data from the tethered speedometer and automated video-based system were exported to Microsoft Excel (.xlsx) and for each trial a region of interest was selected based on the automated video-based system times corresponding to ~10 m and ~20 m. Velocities from both systems at each sampling point between these times were used for statistical analyses. This region of data was selected to mitigate the effects of the push off the wall at the start and potential deceleration at the finish. To examine agreement between the two systems, Bland and Altman plots with bias and limited of agreement (LOA), as well as RMSE were calculated. All statistical analyses were performed in Microsoft Excel 365 (Microsoft Office 365, Microsoft Corporation, Redmond, Washington, United States).

RESULTS: Instantaneous swimming velocities were compared on 9580 data points for each stroke, on average. Figure 1 shows the velocity-time profiles from the automated video-based system and tethered speedometer for each stroke from representative swimmers. The widest LOA and largest RMSE were in breaststroke, whilst the narrowest LOA and smallest RMSE were in backstroke (Table 1). The automated video-based system overestimated instantaneous swimming velocity in all the strokes compared to the tethered speedometer with the largest bias and RMSE reported in breaststroke (Table 1).

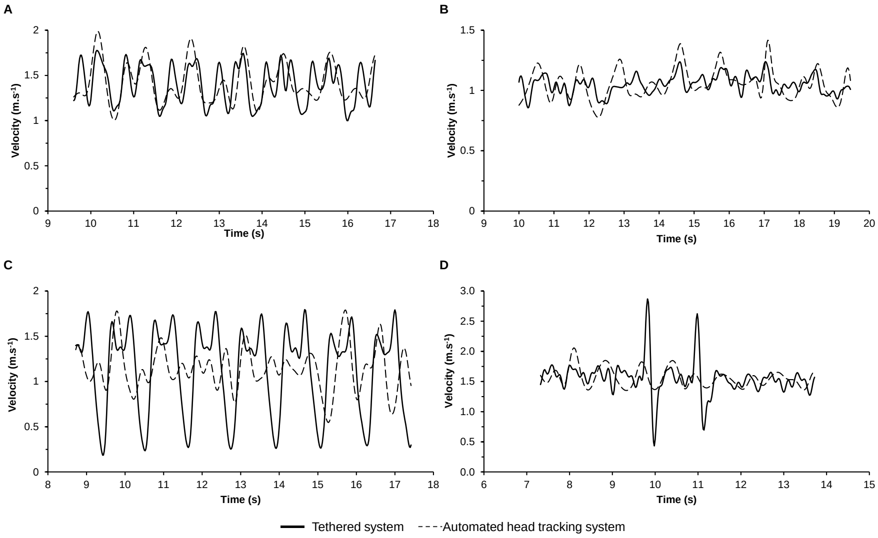

Figure 1: Filtered instantaneous swimming velocity-time profiles from the automated video-based system (dashed line) and tethered speedometer (solid line) for each stroke from representative swimmers (A: butterfly, B: backstroke, C: breaststroke, and D: freestyle). Start and end time of each trace correspond to 10 m and 20 m data from the automated video-based system records.

Table 1: Comparison (mean ± SD) between the instantaneous swimming velocities from the automated video-based system and tethered speedometer for each swimming stroke

Swimming stroke	Bias ($m.s^{-1}$)	95% Limits of agreement		RMSE ($m.s^{-1}$)
		Lower limit ($m.s^{-1}$)	Upper limit ($m.s^{-1}$)	
Butterfly	0.01 ± 0.01	-0.51 ± 0.11	0.53 ± 0.11	0.27 ± 0.06
Backstroke	0.01 ± 0.01	-0.24 ± 0.06	0.26 ± 0.07	0.13 ± 0.03
Breaststroke	0.02 ± 0.04	-0.88 ± 0.23	0.92 ± 0.29	0.46 ± 0.13
Freestyle	0.01 ± 0.01	-0.36 ± 0.07	0.38 ± 0.07	0.19 ± 0.03

Note. Bias represents the difference between the automated video-based system and tethered speedometer instantaneous swimming velocity measurements.

DISCUSSION: This study is the first to examine agreement between an automated video-based system compared to a tethered speedometer. While the bias was similar between strokes (within 0.02 $m.s^{-1}$), differences were noted in the 95% LOA and RMSE. Specifically, the LOA and RMSE were lower for backstroke and freestyle compared to butterfly and breaststroke. Based on these results it was determined that there was good agreement in between the automated video-based system and tethered speedometer during backstroke and freestyle, but poorer agreement in butterfly and breaststroke. These findings show a similar level of agreement to studies that examined agreement in instantaneous velocities between IMUs and tethered systems (Stamm et al., 2013; Clément et al., 2021).

The differences in agreement for the four strokes can be explained by the nature of the stroke, the body segments being tracked, and measurement errors. Specifically, during butterfly and breaststroke a swimmer's body undulates in a wave-like motion using simultaneous arm and leg movements whereas during backstroke and freestyle the arms and legs alternate as the body rotates about the longitudinal axis of the trunk. As such, there is more vertical amplitude of the hips in butterfly and breaststroke (Nicol et al., 2022; Strzała et al., 2017). Furthermore, breaststroke is characterised by a decrease in velocity between the propulsive phases of the arms and legs resulting in the largest intra-cyclic velocity variations of the four strokes (Nicol et al., 2022). The tethered speedometer attached at the hip would likely be more sensitivity to movement during butterfly and breaststroke compared to a video-based system tracking the head. This is evident in the velocity-time profiles in breaststroke, where the large intra-cyclic velocity variations can be seen in the tethered speedometer velocity profile (Figure 1C).

Differences in agreement may also be due to measurement errors in the tethered system, particular in instances where a swimmer may have kicked the tether (Figure 1D).

CONCLUSION: While this study showed acceptable agreement between the automated video-based system and tethered speedometer, it is important to consider the practical application of the system. For example, while the overall bias was low (0.01 ± 0.01m.s^{-1}), in comparison to the tethered system, the automated video-based system underestimated instantaneous swimming velocity in freestyle by as much as 0.36 m.s^{-1} and overestimated by as much as 0.38 m.s^{-1}. These discrepancies between systems could be problematic for coaches, sports scientists, and swimmers who may be using different systems to monitor velocities during training and races. However, knowing such discrepancies exist can help make informed decisions. Furthermore, there is an opportunity for continued development of algorithms to tracking other body segments (i.e., pelvis) and provide prediction equations that will allow for comparison of data from different systems.

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