USING MACHINE LEARNING TECHNIQUES AND WEARABLE INERTIAL MEASUREMENT UNITS TO PREDICT FRONT CRAWL ELBOW JOINT ANGLE: A PILOT STUDY

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This study evaluated the validity of using an artificial neural network (ANN) and inertial measurement units (IMUs) for estimating front crawl elbow angle in a laboratory environment. The study evaluates the validity of two models resulting from two swimmers who adopted different front crawl techniques. For each participant, data were collected from two IMUs placed on the arm during three minutes of ergometer-based swimming. These data were entered into an artificial neural network along with the target data which was elbow flexion angle from a camera-based motion capture system. The performance of each model was assessed by comparing the predicted elbow angle to the gold standard elbow angle during ten front crawl strokes collected separately from the training data. Root mean square difference (RMSD) between predicted and gold standard elbow angle across the ten stroke cycles was 7.75° for both participants. This pilot study demonstrates validity of using IMUs and artificial neural networks in a laboratory environment for estimating front crawl elbow angle in two swimmers who used different front crawl techniques.

KEY WORDS: swimming, front crawl, elbow joint, artificial neural network, IMUs.

INTRODUCTION: Video analysis is the current gold standard method to measure swimming joint kinematics. However, video analysis has several limitations. Results tend to be error-prone due to parallax, water turbulence and hidden body segments. In addition, it is disadvantageous for its long set up time and computational effort which delays real-time feedback to coaches and athletes (de Magalhaes, Vannozzi, Gatta, & Fantozzi, 2015). Recently, advances have been made in using inertial measurement units (IMUs) to measure swimming joint kinematics (Fantozzi et al., 2016). The relatively small size of these units means they can be worn on the body by swimmers for one or more laps and can provide real-time feedback using graphical user interface (GUI) (Le Sage et al., 2011). Of relevance, set up time and computational effort is greatly reduced compared to video analysis (de Magalhaes et al., 2015).
The validity and reliability of IMUs have been investigated using conventional swimming biomechanical parameters (i.e. time, velocity, stroking and kicking) (Callaway, 2015; Dadashi et al., 2013; Davey, Anderson, & James, 2008; Lee, Stamm, Burkett, Thiel, & James, 2011). However, few studies have assessed swimming joint kinematics. For instance, only one study has shown that IMUs can be used to assess front crawl elbow flexion and extension in a dryland environment (Fantozzi et al., 2016). This study found a 15° (12°-17°) root mean square error (RMSE) compared to the gold standard.
In this pilot study, the aim was to evaluate the validity of estimating front crawl elbow angle using artificial neural networks (ANN) and IMU data in lab environment. We hypothesize that an artificial neural network approach will produce acceptable estimations of front crawl elbow angle through the stroke cycle that can be applied in aquatic settings in the future. This paper will evaluate the validity of two different models resulting from two swimmers who adopt different front crawl techniques.

METHODS: One male swimmer (Participant 1; age: 29 years; height: 182 cm; mass: 72 kg; swim experience: 10 years; front crawl technique: straight arm pattern) and one female swimmer (Participant 2; age: 32 years; height: 157cm; mass: 58 kg; swim experience: 12 years; front crawl technique: s-shape pattern) were recruited and gave their written informed consent to participate. The study was approved by the Ethical committee of the University of Queensland.

The validity of the IMU-based method of predicting front crawl right elbow angle was assessed separately in each of the two participants because they adopted the fundamentally different front crawl techniques. In both participants, the IMU-based method was compared in a laboratory environment to a gold standard elbow angle based on 3D motion capture data. The swimmers in this study replicated their in-pool front crawl swimming stroke as closely as possible on a swim bench ergometer (Vasa, Inc., Essex Junction, USA). The ergometer seat carriage was blocked and participants simulated front crawl technique without resistance.

Participants completed two types of swimming test which were required for training and testing the performance of the ANN. First, to train the ANN, IMU and motion capture data were collected during three minutes of continuous swimming strokes. Each minute the swimmer was asked to employ a stroke rate of 60 (0.50 seconds per stroke), 65 (0.46 seconds per stroke), and 70 (0.43 seconds per stroke) strokes per minute (SPM) respectively. These paces are representative of recent Olympic 50m freestyle performance (https://www.tritonwear.com). Stroke rate was tuned using a metronome (Tempo Trainer Pro, FINIS Inc., USA) with each beat corresponding to the approximate moment of hand entry. After a 5-minute rest, data were collected for testing the performance of the method. These data comprised IMU and motion capture data from ten continuous stroke cycles at 65 SPM. Lastly, participants were asked to stand in front of the swim bench ergometer with the arm flexed in the direction of swimming for ten seconds to record IMU data which were used for orientation of the device.

IMU data were collected from three sensors (MuscleLab, Ergotest, Norway) sampling at 200 Hz and consisted of the vectors relating to the IMU accelerations, angular velocities and tilt angles around the x, y, z axes (MuscleLab, Ergotest, Norway). Sensor placement was in line with a previous published validation study (Callaway, 2015). IMUs were attached to the right forearm and right upper arm of each participant using coban self-adherent wrap such that movement and skin artefacts was minimized. A further lower trunk IMU was placed at vertebrae L4 and secured with a waist belt.

Motion capture data were collected using a calibrated six-camera motion capture system (OptiTrack Flex 13, Corvallis, USA) sampling at 120 Hz and were synchronised with IMU data capture using a trigger module (MuscleLab, Ergotest, Norway). The recommendation of the International Society of Biomechanics (ISB) was used to select acromioclavicular joint, lateral and medial humeral epicondyle, and the styloid process of ulna and radius (Wu et al., 2005). Anatomical landmarks were identified by the first author using reflective markers attached to the skin of the participants with a double-sided tape. In addition, two clusters of four markers were positioned midway on upper arm and forearm. A 5 s static trial was recorded and participants were asked to lie on the swim bench ergometer in the anatomical position. During swimming trials no markers were removed.

The right upper arm and forearm models were created in Visual 3D (C-Motion, Germantown, MD, USA). The glenohumeral joint centre was estimated using the method described by Rab (2002). The upper arm was defined anatomically using the estimation of the glenohumeral joint centre and markers on the medial and lateral humerus epicondyles. The forearm was defined anatomically using the distal humerus and the styloid process of ulna and radius. Elbow flexion and extension angles were calculated in Visual 3D using the ISB recommended Cardan sequences (X–Y–Z) with the forearm relative to the upper arm.

An ANN was developed (Matlab R2016b, Mathworks, USA) for each swimmer to predict right elbow flexion angle based on IMU data. ANN input training data comprised the acceleration, angular velocity and tilt angle data from the IMUs. These were smoother using a moving average filter with 50 frame span (Matlab R2016b, Mathworks, USA). The movement of the trunk was minimal on the swim ergometer but any effects of trunk movement was further reduced by subtraction of the trunk IMU data from the arm IMU data. The ANN also received the corresponding target data which was the gold standard elbow flexion angle. The ANN architecture was fully-connected with one hidden layer comprising ten nodes. The input layer and hidden layer were connected using a hyperbolic tangent sigmoid transfer function. The hidden and output layers were connected using a linear transfer function. The scaled conjugate gradient backpropagation algorithm was used to train the ANN from a random initial state. ANN training was terminated when no more improvement in the mean square error between predicted and gold standard elbow angle was observed. Hence, the output of each model was a predicted elbow angle. The performance of each ANN was assessed by applying the derived model to the previously unused IMU data collected from the ten front crawl strokes in the separate trial. The resulting prediction was compared to the gold standard elbow angle. The RMSD between the IMU-derived predicted elbow angle and the gold standard elbow angle was calculated based on these continuous ten strokes.

RESULTS: The RMSD between the IMU-derived predicted elbow flexion angle and the gold standard elbow flexion angle over ten stroke cycles at 65 SPM was 7.75° for both participants (Figure 1).

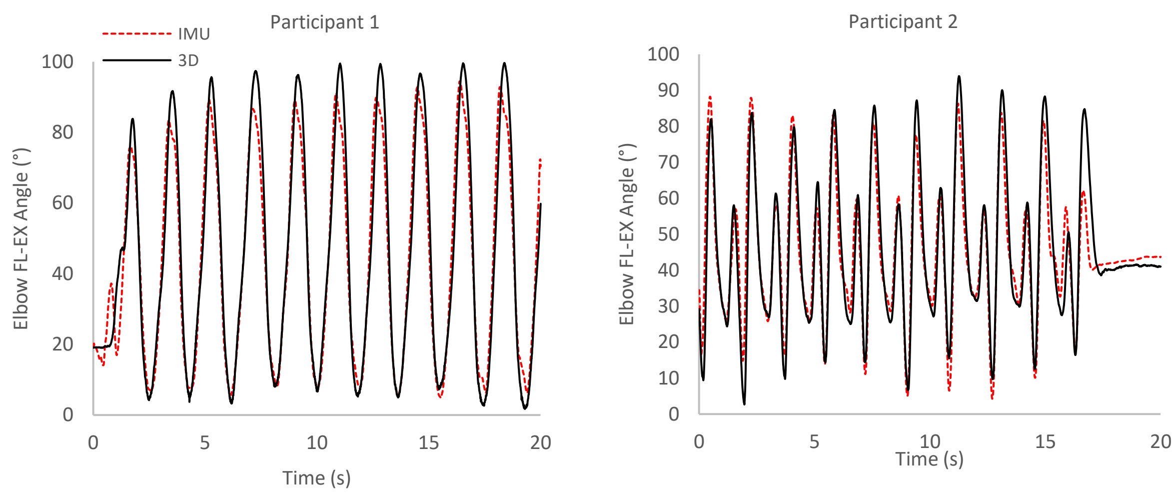

Figure 1: Elbow angle over the ten strokes cycle at 65 strokes per minutes in participant 1 using the straight arm (left) and participant 2 using the s-shape or high elbow (right) front crawl technique.

Further analysis of peak elbow flexion and extension were conducted and results of both front crawl techniques are summarized in Table 1.

Table 1: Comparison of maximum elbow flexion and extension for both front crawl techniques.

	Participant 1			Participant 2	
	3D	IMU		3D	IMU
Maximum Elbow Flexion (°)	94.9±4.8	87.9±5.3	**Maximum 1st Elbow Flexion (°)**	85.3±4.4	80.1±7.5
Maximum Elbow Extension (°)	4.8±2.1	6.8±1.2	**Maximum 1st Elbow Extension (°)**	28.2±4.2	30.0±4.4
			Maximum 2nd Elbow Flexion (°)	58.1±3.9	57.1±1.9
			Maximum 2nd Elbow Extension (°)	11.2±4.3	11.7±5.0

DISCUSSION: This pilot study is the first to report the validity of applying an artificial neural network to IMU data for estimating front crawl elbow angle in two swimmers who adopt different front crawl techniques. The results are encouraging for several reasons. First, the RMSD between predicted and gold standard elbow angle in the two participants was considerably smaller than the RMSD in previous research (Fantozzi et al., 2016). Secondly, the analysis was equally successful at predicting elbow angle in participants using different front crawl techniques. Thirdly, the model was equally successful at predicting elbow angle

in a male and a female. Notably, participant one showed a straight arm technique (Figure 1). In this individual, the IMU-based estimate performed better in maximum elbow extension compared to maximum elbow flexion. On the other hand, participant two showed multi-directional movements resembling the s-shape technique (Figure 1). In this individual, the IMU-based method performed better when estimating maximum elbow extension.
There are limitations to acknowledge in this pilot study. First, swimming is a water sport and as such assessing biomechanical parameters outside the real environment might find limited practical application for coaches and scientists. However, we hypothesize that an ANN will produce acceptable estimations that can be applied in aquatic settings in the future. Secondly, this study included and presented data of only two participants thus warrant larger sample size. Thirdly, at this time the validated models of two front crawl technique are not generalizable.
Preliminary results of this study indicate that two models are perhaps required to estimate elbow flexion angle for each of the front crawl techniques. Further investigations will increase the sample size and evaluate the validity of the two models in an aquatic environment. A greater sample size will permit derivation of a model for each technique and evaluation of the extent to which the models are generalizable for predicting front crawl elbow flexion angle in each of the two techniques investigated. Lastly, it should be acknowledged that further analysis will consider whether the smoothing technique used can reduce the error found in this study.

CONCLUSION: This pilot study demonstrated the validity of using IMUs and an artificial neural network for estimating front crawl elbow angle in two swimmers who used different front crawl techniques. These data warrant data collection in a larger group of swimmers and the application of the ANN models in an aquatic environment.

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