DETECTION OF DIFFERENT THROW TYPES AND BALL VELOCITY WITH IMUs AND MACHINE LEARNING IN TEAM HANDBALL

Roland van den Tillaar[1], Shruti Bhandurge[2], Tom Stewart[2]

Department of Sports Sciences, Nord University, Levanger, Norway[1]
Sports Performance Research Institute New Zealand, Auckland University of Technology, Auckland, New Zealand[2]

The purpose of this study was to investigate if an inertial measurement unit (IMU) and machine learning could be used to detect different types of team handball throws and predict ball velocity. Throwing was measured using IMUs and a radar gun in seventeen participants during standing, running and jump throws with a circular and whip-like wind up. Using these data, machine learning could predict peak ball velocity with an error of 1.05 m/s and classify approach types and throw types with ~85–90% accuracy. It was concluded that to monitor throwing load, the combination of inertial measurement units and machine learning offers a practical and automated method of quantifying throw counts and discriminating throw types in handball players under standard conditions.

KEY WORDS: throwing velocity, artificial intelligence

INTRODUCTION: Handball is large sport with around 20 million competitors worldwide. To excel in handball, athletes need to train a lot; often daily for elite players. However, training can also cause injuries by using bad technique or too much load. Common injuries in handball are shoulder and elbow pain. In handball, 44–75% of the athletes have a history of shoulder pain (Myklebust et al., 2013) and a weekly prevalence of shoulder problems was observed in 28% of athletes (Clarsen et al., 2014; Myklebust et al., 2013). In baseball (an overhead sport with throwing somewhat comparable to handball), half of youth pitchers experience shoulder pain during the season (Lyman et al., 2001; Lyman et al., 2002). Shoulder pain has been reported to have an impact on the athletes' training activities (Clarsen et al., 2014; Mohseni-Bandpei et al., 2012; Myklebust et al., 2013), performance, and daily life (Myklebust et al., 2013).

One of the risk factors for shoulder and elbow injuries is training load (overtraining and undertraining). To monitor over- and undertraining, several studies have tried to quantify workload during training and competition (Gabbett et al., 2014; Stewart & Hopkins, 2000). The importance of monitoring workload in athletes is corroborated by research supporting a positive relationship between workload and injury (Gabbett, 2004). Although it is hypothesised that restricting workloads may minimise the likelihood of athlete injury, reducing workloads in competition and training may also be detrimental to an athlete's conditioning and performance (Gabbett, 2004). Global position systems (GPS) have been used to measure workload (Coutts et al., 2010; Spencer et al., 2004); however, GPS cannot measure throwing-related load, only whole body velocity and acceleration.

In recent years, inertial measurement sensors (IMU) have been used to identify the number of throws in baseball and cricket and these microtechnology units are increasingly used as a reliable and accurate method of monitoring athlete workloads (Cummins et al., 2013). To our knowledge, no device exists that has been validated for handball use. The advantages of IMUs are that they are light, inexpensive and easy to use during competition in different sports compared with traditional 3D analysis equipment. In handball, there is the added challenge of different types of throws and passes that occur during training and competition. However, artificial intelligence techniques could potentially monitor the number, types, and speed of throws automatically using IMU data. The aim of this study was to investigate the efficacy of machine learning algorithms for detecting different throwing techniques from wrist-worn IMU data, and the accuracy of predicting ball velocity.

METHODS: Seventeen experienced handball players (10 men and 7 women; age 28.0 ± 7.3 years, body mass 74.4 ± 13.6 kg, body height 1.77 ± 0.09 m) were recruited for the study. Data collection was performed across two testing sessions. After a warm-up, all participants performed standing, running, and jump throws with either a circular or whip-like wind-up (van den Tillaar et al., 2013). These were performed 7 m from a standard handball goal (2 x 3 m). They performed 7–10 throws in each condition, which were randomised; thus, 49–60 throws were collected per subject. Six subjects performed the throws on both test days.

A wireless 9 degrees of freedom inertial measurement unit (IMU) containing a 3-axis accelerometer (±16 g, sampling frequency 1125 Hz), integrated with a 3-axis gyroscope (± 2000°/sec, 1125 Hz) and a magnetometer (range ± 4900µT, 100 Hz) was attached to the distal dorsal side of the throwing arm (IMeasureU, Auckland, New Zealand). Peak ball velocity was measured by a Doppler radar gun (Stalker ATS II, Applied Concepts Inc., Plano, TX). The radar gun was located 11 m away from the handball goal, with a straight line between the target, the thrower, and the gun. It measured speed with an accuracy of 0.028 m/s within a 10° field. All testing sessions were recorded by two video cameras.

The accelerometer and gyroscope data were resampled to 1150 Hz using linear interpolation, given a small sampling frequency fluctuation among sensors. Throwing events were recognised using a peak detecting algorithm with a 1500°/sec threshold on the gyroscope y-axis. Acceleration and rotational properties of each throw were calculated within a 6 s window around each throw (3 s either side of the peak rotation), including axis means, variance, power, amplitude, autocorrelation, skewness, kurtosis, and between-axis correlations. In total, 134 signal features were computed for each throw.

Using the signal features, two supervised machine learning classification models using a random forest algorithm (Breiman, 2001) were trained to predict the different throw types (whip-like or circular) and the approach (standing, running, or jumping). Both models used n = 150 trees, and m = 5 (the number of features tried at each split point in each tree). The predictive accuracy of each model was estimated using k-fold cross-validation, and the sensitivity, specificity, and balanced accuracy (mean of sensitivity and specificity) was calculated for each predicted category. Next, a regression-based random forest was used to predict ball speed (m/s). This model also used 150 trees, but the optimal m parameter was 30. Prediction error was estimated via cross-validation, and both root mean squared error and mean absolute error metrics were computed.

RESULTS: The main peak ball velocities was 21.1±2.5 m/s with some differences between the type of throws (Table 1). The accuracy of classifying the approach type (jump, running, standing) was 89.7% (95% CI, 87.6–91.6). The sensitivity, specificity, and balanced accuracy for each approach type are shown in Table 1.

Table 1. Mean ± SD for speed of the different throw and approach types and classification of approach type.

	Standing		Running		Jump	
	Circle	Whip	Circle	Whip	Circle	Whip
N	184	182	182	182	116	116
Velocity (m/s)	20.7±2.6	20.1±2.5	22.0±2.4	21.2±2.4	21.4±2.5	21.0±2.4
Sensitivity (%)	92.1		85.7		92.7	
Specificity (%)	91.9		94.1		97.9	
Balanced accuracy (%)	92.0		89.9		95.3	

The accuracy of classifying the throw type (circular or whip-like) was 85.1 (95% CI, 82.7–87.3). This model has reasonably high sensitivity (82.4%), specificity (88.3%), and balanced accuracy (85.4%). The most important signal features for predicting throw type were the mean and sum of the gyroscope x-axis (movement in sagittal plan), and the standard deviation of the accelerometer z-axis (Fig. 1).

Our random forest model was able to predict ball speed with a root mean squared error of 1.05 m/s and mean absolute error of 0.78 m/s. The most important signal features for predicting ball velocity were the amplitude of the gyroscope z-axis, and the standard deviation of the accelerometer x-axis (Fig. 1).

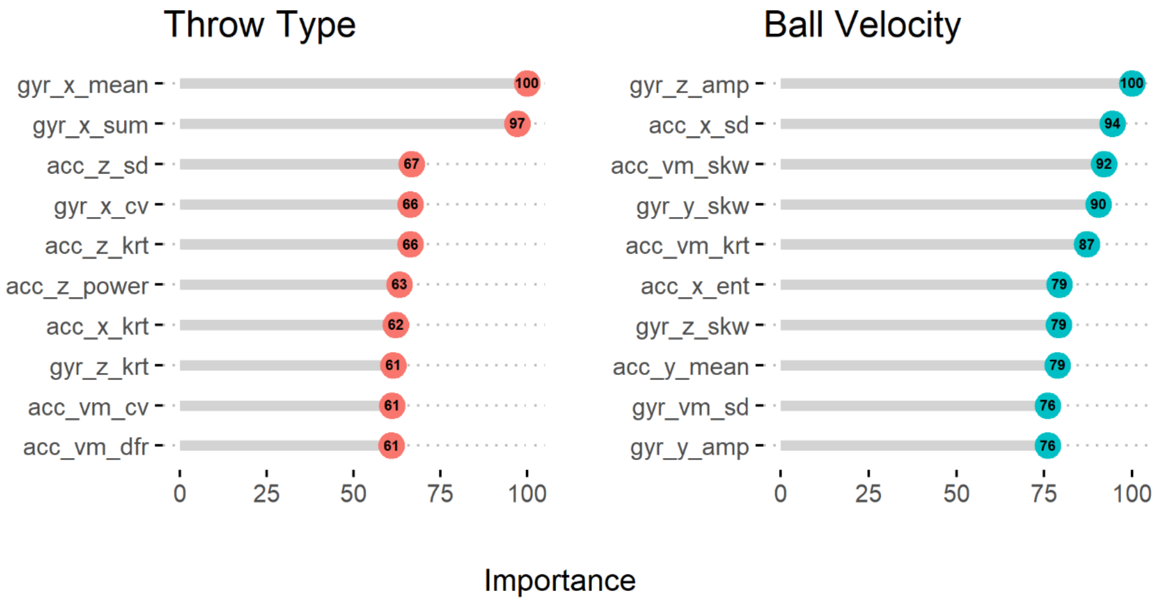

Figure 1. Relative signal feature importance for predicting throw type and ball velocity.
Note: The prefix indicates the accelerometer (acc) or gyroscope (gyr) sensor, the middle character is the axis (x, y, z, or vector magnitude), and the suffix indicates the feature: cv=coefficient of variation, skw=skewness, krt=kurtosis, dfr=dominant frequency, amp=peak-to-peak amplitude, ent=entropy.

DISCUSSION: The main findings were that the IMU data coupled with machine learning algorithms could predict peak ball velocity with an error of 1.05 m/s and that approach types and throw types could be classified with ~85–90% accuracy. The detection percentage of the different throws was a bit lower compared with a comparable study (93–97.4%) in tennis (Whiteside et al., 2017). This could be due to the number of throws that were tested (962 throws vs. 28582 shots), which makes it possible to develop a more accurate model. Furthermore, the level of the athletes in the present study were not elite players with a lot of experience in the whip-like wind-up throwing technique. Due to this inexperience, sometimes they struggled with the whip-like wind-up technique, meaning some throws of different types looked very similar. Therefore, elite-level players that can perform all throwing techniques accurately should be included in future work.

The error of the peak ball speed between the radar gun and the IMU measurements was 1.05 m/s, which could be less when the throws are directed straight towards the goal (3 x 2 m). Some throws were aimed at the corner or outside the goal and thereby cause an angle larger than 10 degrees with the radar gun. This probably resulted in lower peak velocities, since the radar gun only measures the horizontal displacement to the goal. In future studies, a smaller target (0.5 x 0.5 m) should be used to gather more accurate radar gun readings. It is also likely the low resolution (±16 g) of the accelerometer affected the ball velocity prediction accuracy. A higher resolution sensor (e.g. ±200 g) may provide higher accuracy.

The main limitation of the present study was that the handball throws were conducted in a standardised situation without any opposition or time limitations. In handball training and competition, the different throws are almost never standard, except with a penalty throw. Furthermore, handball throws can be divided in shots to the goal and passes to each other. These differences were not taken into account in the current study. Therefore, the methods used in this study should be tried in handball training and competition to investigate if it is possible to detect the different throwing/passing styles and approaches under these circumstances.

CONCLUSION: Based upon the findings of the present study we can conclude that under standard conditions, IMUs and machine learning could predict peak ball velocity and that the approach types and throw types were detectable. With a view to monitoring external load, the combination of miniature inertial sensors and machine learning offers a practical and automated method of quantifying throw counts and discriminating throw types in handball players under standard conditions.

REFERENCES

Breiman, L. (2001). Random Forests. *Machine Learning,* 45, 5-32.

Clarsen, B., Bahr, R., Andersson, S. H., Munk, R., & Myklebust, G. (2014). Reduced glenohumeral rotation, external rotation weakness and scapular dyskinesis are risk factors for shoulder injuries among elite male handball players: a prospective cohort study. *British Journal of Sports Medicine,* 48, 1327-1333.

Coutts, A. J., Quinn, J., Hocking, J., Castagna, C., & Rampinini, E. (2010). Match running performance in elite Australian Rules Football. *Journal of Science and Medicine in Sport,* 13, 543-548.

Cummins, C., Orr, R., O'Connor, H., & West, C. (2013). Global positioning systems (GPS) and microtechnology sensors in team sports: a systematic review. *Sports medicine,* 43, 1025-1042.

Gabbett, T. J. (2004). Reductions in pre-season training loads reduce training injury rates in rugby league players. *British journal of sports medicine,* 38, 743-749.

Gabbett, T. J., Whyte, D. G., Hartwig, T. B., Wescombe, H., & Naughton, G. A. (2014). The relationship between workloads, physical performance, injury and illness in adolescent male football players. *Sports medicine,* 44, 989-1003.

Lyman, S., et al. (2001). Longitudinal study of elbow and shoulder pain i youth baseball pitchers. *Medicine & Science in Sports & Exercise,* 33, 1803-1810.

Lyman, S., Fleisig, G. S., Andrew, J. R., & Osinski, E. D. (2002). Effect of pitch type, pitch count, and pitching mechanics on risk of elbow and shoulder pain in youth baseball pitchers. *American Journal of Sports Medicine,* 30, 463-468.

Mohseni-Bandpei, M. A., Keshavarz, R., Minoonejhad, H., Mohsenifar, H., & Shakeri, H. (2012). Shoulder pain in Iranian elite athletes: the prevalence and risk factors. *Journal of manipulative and physiological therapeutics,* 35, 541-548.

Myklebust, G., Hasslan, L., Bahr, R., & Steffen, K. (2013). High prevalence of shoulder pain among elite Norwegian female handball players. *Scandinavian Journal of Medicine & Science in Sports,* 23, 288-294.

Spencer, M., et al. (2004). Time-motion analysis of elite field hockey, with special reference to repeated-sprint activity. *Journal of sports sciences,* 22, 843-850.

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

van den Tillaar, R., Zondag, A., & Cabri, J. (2013). Comparing performance and kinematics of throwing with a circular and whip-like wind up by experienced handball players. *Scandinavian journal of medicine & science in sports,* 23, e373-380.

Whiteside, D., Cant, O., Connolly, M., & Reid, M. (2017). Monitoring Hitting Load in Tennis Using Inertial Sensors and Machine Learning. *International Journal of Sports Physiology & Performance,* 12, 1212-1217.