

ORIGINAL ARTICLE



Standing Handball Throwing Velocity Estimation with a Single Wrist-Mounted Inertial Sensor

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ABSTRACT

Background. It is well known that overarm throwing is one of the most performed activities in the handball. Shoulder and glenohumeral injuries incidence are high in handball because of both pass, and shooting activity was executed repeatedly in high angular speed. **Objectives.** This study set out to investigate the usefulness of inexpensive commercial inertial movement sensors for prediction of throwing velocity in handball. **Methods.** After the IMU sensor (500 Hz) placed to the wrist of the dominant arm, players (n=4; 24.4 ±1.4 years, 181.75 ±11 cm height, 84.58 ±16 kg weight) performed 30 standing overarm throwing from a seven-meter distance with 1-minute rest between trials. Throwing velocity compared between radar speed gun and estimations of accelerometer data. Recorded acceleration data filtered (Butterworth 20 Hz 2nd order) than the acceleration vector magnitude calculated. Each throwing data aligned such as 125 data points of before and after the peak acceleration (250ms). Performance metrics of prediction models (Generalized Linear Model, Gradient Boosted Trees, and Support Vector Machine) calculated with root mean square, absolute error, and correlation coefficient parameters. **Results.** There were reasonably small absolute errors and root mean square values of the machine learning models. Also, there was a very high correlation between measured and predicted velocities with all three models. **Conclusion.** This is the first study to examined machine learning models to predict handball throwing velocity using a high-frequency triaxial accelerometer. The finding of the present study revealed that the wrist-attached accelerometer precisely estimates the throwing velocity in handball. Further research is required to quantifying the overarm activities in handball, which included block, defensive contact, passing, or shooting. Therefore, the accelerometer-based collected data may provide detection of movement in game-play automatically so that the upper extremity load of players can be monitored and avoid the possible overuse injury risk.

KEYWORDS: *Inertial Sensor, Tri-axial Accelerometer, Machine Learning, Throwing Velocity*

INTRODUCTION

It is well known that overarm throwing is an important aspect of score a goal in the handball. Besides the being a key performance indicator, overarm throwing generates a high level of upper extremity load for players depending on several executions in a high-velocity shooting. Shoulder and glenohumeral injuries incidence are high in handball due to both pass, and shooting activity was executed repeatedly in high angular speed (1,

2). Therefore, measuring throwing velocity is essential both for the success of shooting and also the management of load monitoring. European Handball Federation has made a partnership with a sports-tech company KINEXON that allow to ball tracking in real time. SELECT-manufactured iBall enables to capture ball speed, shooting position and ball placement on the goalie (3). However, the iBall system based on the ultra-

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wideband technology that needed to court specific setup. Therefore, it is limited to special events or courts that initialized before the competition. There are numerous throwing velocity measurement methods such as radar speed gun (4, 5), motion capture (6, 7), photocell system (8, 9) in the applied settings. To our knowledge, there are no gold standard methods to assessment of throwing velocity. The 3-D motion analysis is research-grade method and usage in the field is very rare. Although this laboratory-based measurement is precise and accurate, it is limited to require expensive devices, expert staff to use it, and long assessment and interpretation time. On the other hand, commonly used methods in the field are radar gun and photoelectric system. However, throwing velocity assessment using these methods involve the players perform to a target. Nevertheless, previous studies have indicated that decreases in the throwing velocity in case of instructed to perform against a target (10, 11). As a result of this accuracy velocity trade-off, the measured velocity may not show the exact load of the shoulder. Another disadvantage of these methods is not to involve a goalkeeper or defensive opponent due to applied settings, which cause challenging the simulating game-like activities. Recently, accelerometer and IMU-based wearable technology emerged to use for overarm throwing performance assessment. Previous studies have revealed that wearable sensor's motion capture abilities, for instance, quantified the throwing activity (12), kinematic analysis of overarm throwing and comparison with lab-based systems (13, 14). However, the accelerometer-based throwing velocity evaluation has only been established in one study with a low sampling frequency (250 Hz) (15). Moreover, the results of this study showed average prediction success attained from accelerometer data. Therefore, the aim of this study was to predict the throwing velocity by using wrist-mounted inertial sensors in handball.

MATERIALS AND METHODS

Study Design. Four (one female and three male; 24.4 ± 1.4 years, 181.75 ± 11 cm height, 84.58 ± 16 kg weight) experienced handball players volunteered to participate in this study. Before the experiment, participants provided written informed consent in accordance with the Declaration of Helsinki. All participants were trained at least six years in a senior team level. The study protocol was approved by the local ethical

committee (2019/13-54). Steps from performing a total of 120 throwings and data processing showed as an algorithm in the Figure 1.

Throwing Velocity. The players performed 10-minute general and 10-minute special (included passing and shooting exercises) warming up. Participants performed 30 standing overarm throwings from a seven-meter distance with official handball ball (males: 58 - 60cm in circumference and 425 - 475g, females: 54 - 56cm in circumference and 325 - 375g) with 1-minute rest between each throwing. During the overarm throwing, at least one feet of the player must contact the floor and this pivotal feet must be behind the throwing line.

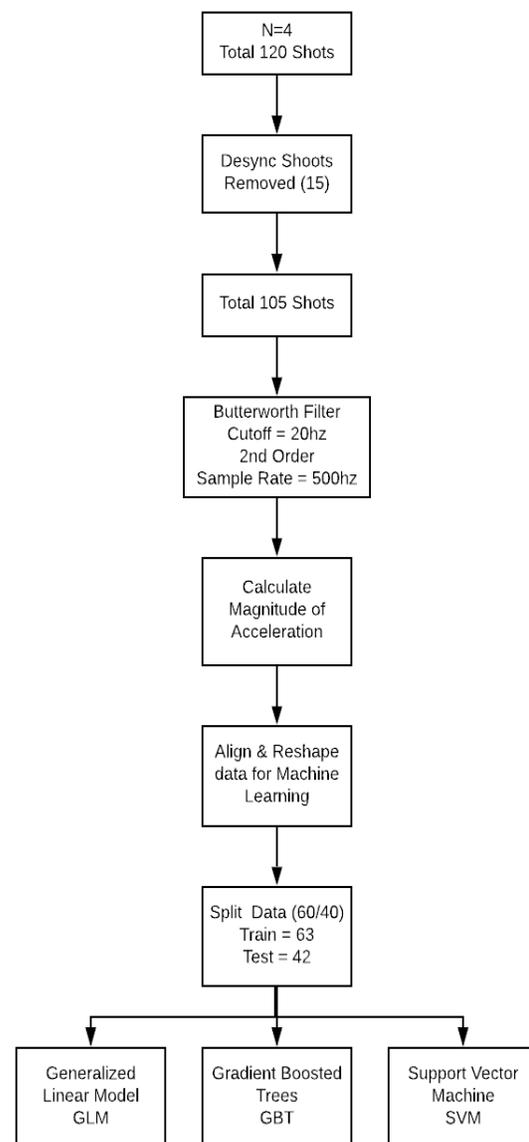


Figure 1. Flowchart for the Process Included from throwing to prediction.

The triaxial accelerometer (the Notch system, Notch Interfaces Inc.) was attached to distal part of player's dominant wrist via elastic wrist band (Figure 2). Radar speed gun (Bushnell Speedster III Radar, Japan) was placed behind the goal at 1.65 m height in the middle, 12 m distance to throwing line (7-meter line). Players were asked to stay stationary before throwing and perform with an instruction. After the instruction, players were asked to throw as fast as possible straight to the middle of the goal. The throwings which started before the instructions considered as desync and excluded from estimation. Throwings which performed within >10 degrees from radar gun were also excluded.



Figure 2. Demonstration of Throwing the Ball with Wrist-Mounted Accelerometer

Accelerometer Data. Before the testing, the notch system sensor was calibrated as described by the manufacturer's instructions. In the pilot assessment, the sampling rate was 100 Hz, such as the implementation of commercial accelerometers (16-18). However, because of overarm throwing movement is performed at high angular speed, it has been revealed that accelerometer data have low resolution and cannot capture peak acceleration (Figure 3). Therefore, application of the notch system sensor adjusted to record maximum 5 s with a 500 Hz sampling rate. After the transfer of

recorded acceleration data to a computer via Bluetooth, Butterworth 20 Hz 2nd order filter applied and gravitation free raw acceleration data has been used for estimation. Acceleration vector magnitude calculated by using the formula:

$$a_{mag} = \sqrt{a_x^2 + a_y^2 + a_z^2}$$

The two-dimension accelerometer data reshaped as one dimension and randomly separated to train and test in proportion to %60/40 (63/42 throwing). Prediction models attained from processed data via Generalized Linear Model (GLM), Gradient Boosted Trees (GBT), and Support Vector Machine (SVM). Performance metrics of prediction models calculated with root mean square, absolute error, and correlation coefficient parameters.

Statistical Analysis. Preparing, debugging, and visualization of data was executed with MATLAB (MATLAB and Statistics Toolbox Release 2018, The MathWorks, Inc., Natick, Massachusetts, United States). Machine learning models were applied by RapidMiner framework (19).

RESULTS

Throwing velocities measurements have been distributed between 60-84 km/h (Figure 5). Relationship between measured and predicted throwing velocities have been shown at Figure 6. Performance metrics of machine learning models GLM, GBT, and SVM were presented at Table 1.

As shown in the Table 1, machine learning methods showed very high correlation. However, there was a higher correlation and lower absolute error in General Linear Model in comparison to the Gradient Boosted Trees and Support Vector Machine methods.

DISCUSSION

This study set out to predict the velocity of standing overarm throwing by using a triaxial accelerometer. The current study indicates that standing throwing velocity measurement via IMU sensor very highly correlated with traditional radar gun assessment. The finding of the present study suggests that as a wearable product wrist-attached accelerometer precisely estimate the throwing velocity in handball.

Previous studies that evaluating overarm throwing velocity have executed with methods before mentioned such as motion capture (6, 7), photocell system (8, 9), and radar speed gun (4, 5). In reviewing the literature, there was limited data on

the measurement of throwing velocity by using the accelerometer (15). In accordance with the present results, Skejo and et al. found that forearm attached accelerometer can estimate the ball velocity with acceptable accuracy ($r^2 = 0.71$) (15). However, the high-level range of error (6.49 - 8.44 m/s) in the throwing velocity in this study contradicted with present results. The observed difference between the accuracy of these studies may be explained by they used a lower sampling rate (250 Hz). Moreover, they have single feature created to the estimation of throwing velocity from accelerometer data and after determined to predictive performance with the method of linear regression. Whereas in the present study, 125 data points of before and after the peak acceleration consider as input via data alignment (Figure 4). Additionally, this result showed that adjusting the higher level of accelerometer sampling frequency is important to the analysis of high-intensity activities. It must be considered in the team sports player load management during the high impact challenges of two players, which resulted in an isometric contraction. Luteberget and et al. also

underlined this possible miscalculation of the accelerometer, which pivot and defensive challenges are a high impacted activity (20).

In respect to team sports, most IMU-derived assessments have focused on evaluating locomotor demands of the nature of sports for instances volleyball jumping, rugby tackling, and soccer goalkeeping (21). Nowadays, applications of the wearable accelerometer technology to identify sport specific motions may be beneficial to injury prevention. In the literature, most of these sport specific activity predictions via accelerometers conducted in baseball. Murray and et al. have observed the wearable microtechnology unit detected to baseball throwing a pitching movement (12). Results showed that wearable microtechnology unit detected the pitching and throwing movement during training and match; however, did not succeed to differentiate between these movements. A possible explanation for this might be that low sampling rate. Also, contradict to wrist-mounted wearable products, they placed the accelerometer body with a vest.

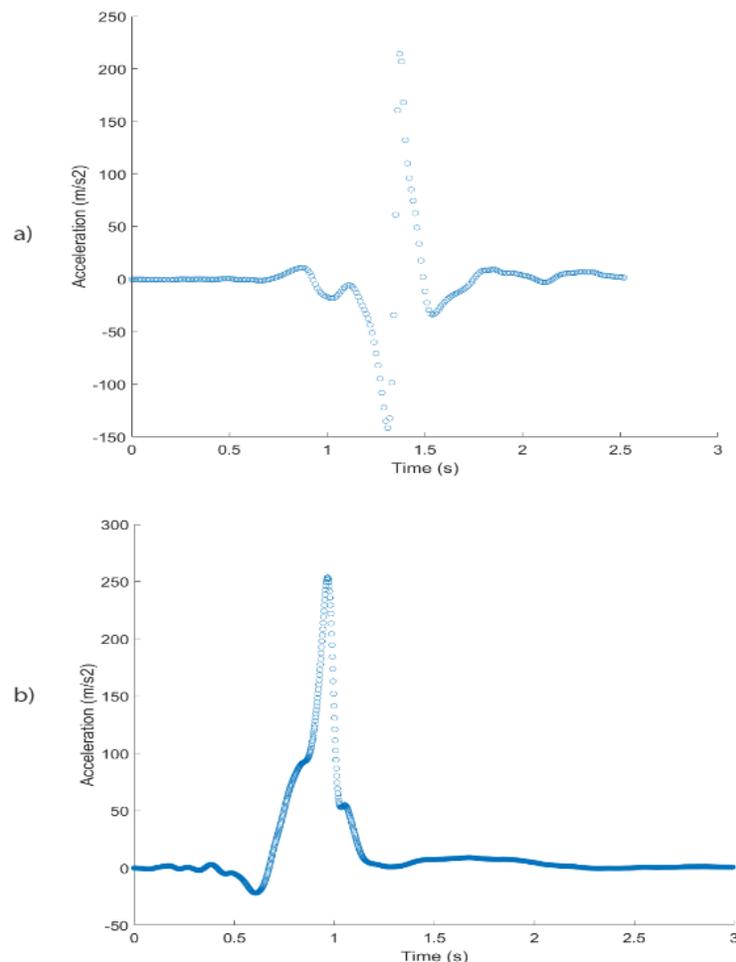


Figure 3. A Sample Data from Accelerometer; a) 100 Hz Sampling Rate; and b) 500 Hz Sampling Rate

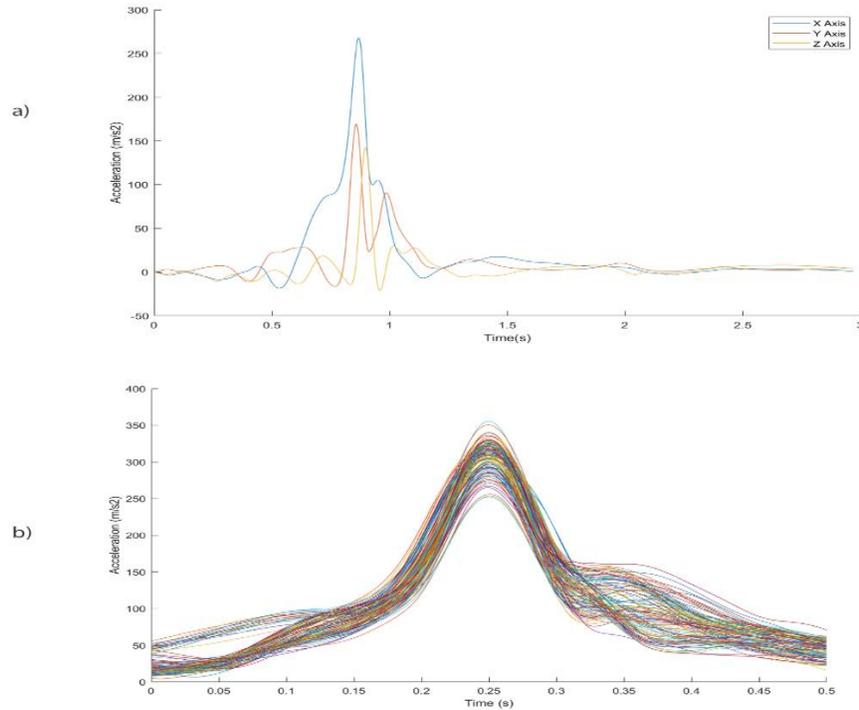


Figure 4. Data Visualisation of Accelerometer a) One Throwing Data; and b) Whole Collected Data in Format to Align.

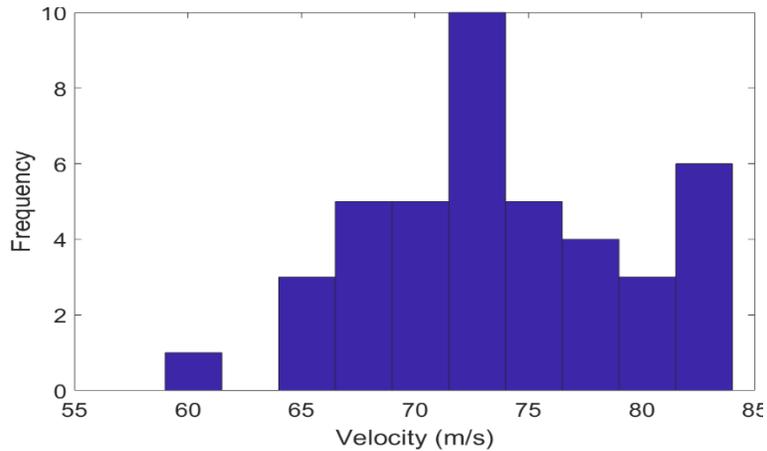


Figure 5. Distributions of Throwing Velocities (km/h).

Table 1. Performance Metrics of the Machine Learning Models

	Correlation	SD ±	RMS	SD ±	Absolute Error	SD
GLM	0.943	0.034	2.34	0.571	1.869	0.407
SVM	0.909	0.04	2.351	0.593	2.069	0.568
GBT	0.927	0.043	2.365	0.469	1.889	0.374

GLM: generalized linear model, GBT: gradient boosted trees, and SVM: support vector machine

In another study, Koda and et al. compared to baseball pitching activity between motion capture with a forearm and upper arm mounted sensors (13). The results suggested trajectories of

shoulder, elbow, and wrist could estimate within 10 % measurement error by using sensors. Acceleration of the body may cause the estimation error. In other study on the overarm

throw, Camp and et al. have reported the relationship between elbow torque and arm rotation with baseball pitching derived load and injury risk in Professional baseball pitchers (22). The application of the inertial sensors to the professional sports has reached a large number of throws in this study and showed that increase of elbow varus torque associated with arm mechanics. Furthermore, Boddy and et al. recently examined the validation of the inertial

sensor to a biomechanical analysis of baseball pitching (14). They have demonstrated the differences between elbow mounted “Motus BASEBALL sensor” for the joint angle measurements. These findings may be somewhat limited by only examined to the biomechanical analysis of the throwing movement or the quantifying the throwing activity using the accelerometer.

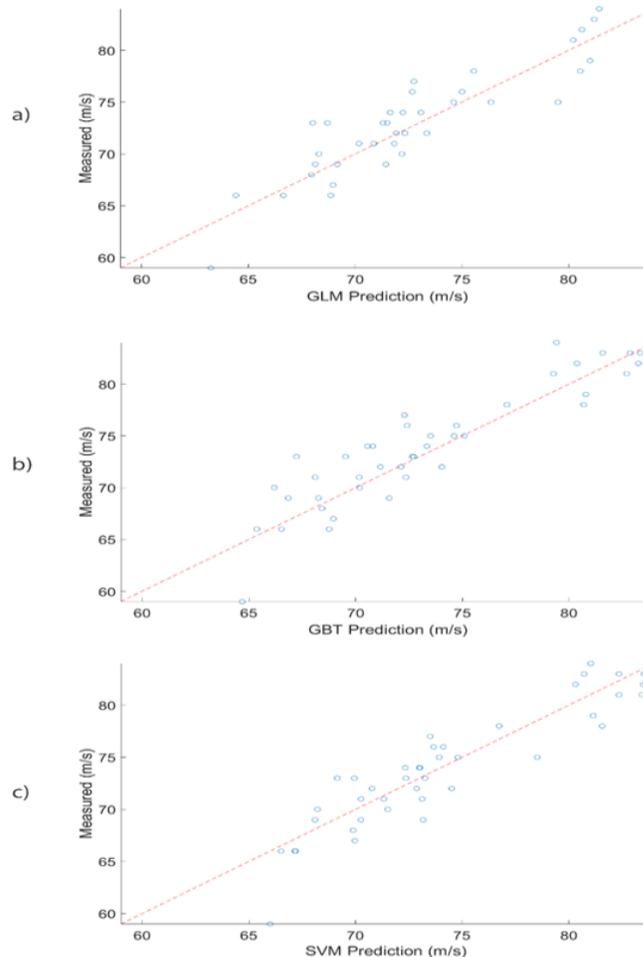


Figure 6. Scatter Plots of Predictions of Machine Learning a) general linear model, b) gradient boosted trees and c) support vector machine models for throwing velocities

According to other disciplines of sports included throwing activities, Wang and et al. have investigated to determine the skill level of volleyball players during spike activity using an inertial sensor (23). Even the IMU placement and data processing was similar to the method of the present study, accelerometer data compared with a high-speed camera. Results showed that the IMU sensor successfully evaluated the volleyball

spike activity, considering the skill level of the players. Moreover, inertial sensors utilized to a kinematic analysis of discus throwing (24). Interestingly McGinnis and Perkins have examined ball embedded wireless IMU for ball velocity and angular velocity of the ball in baseball and softball pitching (25). The finding of this study suggested that sensor technology can determine the ball velocity when compared to

standard motion capture analysis. Also, they observed that the inertial sensor could measure the angular velocity of the ball.

A limitation of this study is that the assessment of throwing velocity conducted only standing to throw. However, 3-step throwing and jumping throwing are also performed in a handball game. Besides the radar gun method, determination of ball velocity via motion capture is one of other limitation. Comparison of different ball velocity assessment methods would be more meaningful for sensor technology. In addition, this current study is limited by the small sample size. Regarding the results of these studies that using IMU sensors for identifying sport-specific movement and kinematic analysis of the overarm throwing, surprisingly there is no study in particular with handball (26). In the future, the prediction of the throwing velocity from accelerometer data would be a reference methodology. Additionally, peak acceleration data which described in this study suggest that detect the throwing activity in the big data collected from handball matches or game-like activity.

CONCLUSION

In the present study, results indicated that the data gathered from accelerometer has precisely estimated throwing velocity with using machine learning models. In the overarm throwing velocity assessment instead of motion capture method, a small and cheap wrist mounted accelerometer could be used in the handball. Further research is required to quantifying the overarm activities in handball, which included block, defensive contact, passing, or shooting. Therefore, the accelerometer based collected data may provide detection of movement in game-play

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automatically so that upper extremity load of players can be monitored and avoid the possible overuse injury risk. In the future, specifically aimed to determine the ambulatory throwing velocity using a wrist-mounted accelerometer seems to be a topic in the field.

APPLICABLE REMARKS

- A tri-axial accelerometer is a novel tool for the prediction of overarm throwing in handball.
- Results showed that a high sampling rate of the accelerometer is an important factor during high angular velocity activities, for instance, overarm throwing.
- The estimation algorithm of inertial sensors' raw data (Machine learning models without features) can be considered a reference method for throwing velocity prediction.

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DISCLOSURE

There are no conflicts of interest in this paper. This study was not supported by any sources of funding. The authors whose names are listed in this paper certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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