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SOCIETY FOR SCIENCE AND EDUCATION

Comparison of Machine Learning Algorithms for Ball Velocity Prediction in Baseball Pitcher using a Single Inertial Sensor

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ABSTRACT

Ball velocity of pitching is an important factor in baseball players. Commonly, ball velocity measurement requires specific devices such as radar gun. On the other hand, Gomaz et al. developed the accurate ball velocity measurement using two inertial sensors on pelvis and trunk. Recently, smartphone installed inertial sensor is popular device in daily life. Therefore, if ball velocity can be measured by only a single inertial sensor, baseball players can measure own ball velocity by only smartphone in daily life and various situations. Thus, the objective of this study is to propose and evaluate the ball velocity prediction method using the only a single inertial sensor. The proposed method predicts ball velocity using by a single inertial sensor and machine learning technique. Five machine learning algorithms (linear regression, support vector machine, gaussian process, artificial neural network, and M5P) predicted ball velocity by data of single inertial sensor, body height, and body weight. In this study, Gomaz et al.'s public data for ball velocity and inertial data during pitching of baseball players were used for this investigation. Sensor placement was either sternum or pelvis. Accuracy of prediction was evaluated by root mean square error (RMSE) between actual and predicted value via leave-one-out cross-validation. The results showed that greatest algorithm (M5P) could accurately predict ball velocity by only single inertial sensor and body parameters (RMSE < 2.0 mph). These results suggest that ball velocity can be measured by only single inertial sensor such as smartphone.

Keywords: Ball Velocity; Prediction; Machine Learning; Inertial Sensor.

INTRODUCTION

The ball velocity of pitching is an important factor in baseball players [1–3]. For example, increasing pitching the ball velocity contributes to delay the batter's reaction time [1]. In addition, Whiteside et al.'s reported possibility that maximum ball velocity contributed to success of pitchers [2]. Furthermore, the ball velocity was useful for rehabilitation program of elbow in baseball pitchers [3]. From these backgrounds, to measure ball velocity during practice is important for baseball pitcher.

Commonly, the ball velocity measurement requires specific devices such as radar gun [4]. In addition, sensor-based instrumented ball was developed to measure ball velocity [5]. The measurement method for ball velocity without specific devices is necessary for that various players understand own ball velocity in daily practice. Gomaz et al. developed the

measurement method for ball velocity using two wearable inertial sensors [4]. An inertial sensor is installed on smartphone that is popular device in daily life, and inertial data obtained from smartphones is was useful to measure sports activities [6–8]. Therefore, if ball velocity can be measured by only a single inertial sensor, baseball players can measure own ball velocity by only smartphone in daily life and various situations. Thus, the objective of this study is to propose and evaluate the ball velocity prediction method using the only a single inertial sensor.

Ball Velocity Prediction

Figure 1 shows the ball velocity prediction method using the only a single inertial sensor. This method predicts ball velocity by machine learning technique and inertial sensor on trunk or pelvis. Usefulness of these sensor placements were founded by Gomaz et al.'s study [4]. In this study, these placements are compared to reduce number of sensors.

Machine learning technique is applied for the proposed method because machine learning technique is known as effective to understand various baseball parameters such as sabermetrics and kinematics [9–11]. Furthermore, Gomaz et al.'s method for ball velocity prediction used machine learning techniques too [4]. In this study, common five machine learning algorithms (linear regression, support vector machine, gaussian process, artificial neural network, and M5P) are compared for the proposed method using a single inertial sensor. Euclidean norm of peak angular velocity obtained from inertial sensor was used for feature of machine learning techniques. Body height, body weight, and age were used features too. These features were selected based on Gomaz et al.'s dataset that was used for training data [4].

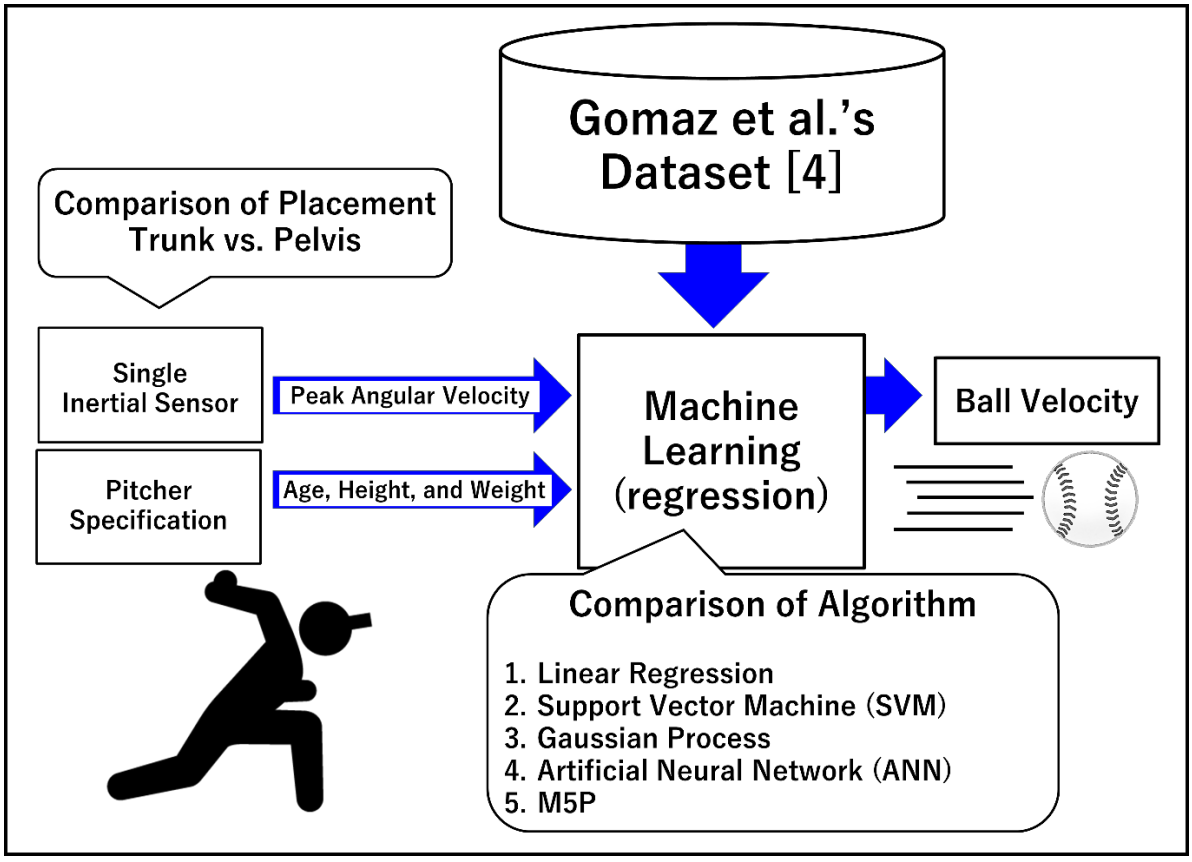


Figure 1. Overview of the Ball Velocity Prediction using a Single Inertial Sensor.

EVALUATION

This study evaluated whether the proposed method could predict the ball velocity using a single inertial sensor. Gomaz et al.'s dataset [4,12] was used for this evaluation. In this dataset, there are inertial data on trunk (sternum) and pelvis for total 224 fastball pitches performed from 25 baseball players (14.7 ± 1.5 years) [4,12]. In addition, this dataset include age, body height, body weight, and actual ball velocity obtained from radar gun[4,12].

Linear regression, support vector machine (SVM), gaussian process, artificial neural network (ANN), and M5P as machine learning algorithm were implemented and evaluated by the Waikato Environment for Knowledge Analysis (WEKA) [13]. The M5P is the regression algorithm using combination of model tree and liner regression [14]. The parameters of SVM and ANN are shown in Table 1 and Table 2. Accuracy of prediction was evaluated by root mean square error (RMSE) between actual and predicted value via leave-one-out cross-validation. These values were compared to explore suitable sensor placement and algorithm. The suitable combination of sensor placement and machine learning algorithm was decided these processes. The proposed method using suitable combination was analyzed by statistical test and the Bland-Altman plot [15,16]. The significant difference between the actual and predicted method was investigated by t-test. Fixed error of prediction [15] was investigated by limits of agreement (LOA) in the Bland-Altman plot. There is fixed error when LOA does not include zero [15]. Proportional error of prediction [16] was investigated correlation between difference (vertical axis) and mean (horizontal axis) in the Bland-Altman plot. There is proportional error when there is significant correlation between the vertical and horizontal axis in the Bland-Altman plot [16]. Correlation between the vertical and horizontal axis was evaluated by correlation coefficient. Significant level was $p < 0.05$. These statistical analyses were performed by the R and EZR [17].

Table 1. Parameters of Support Vector Machine

Option / Parameter	Status / Value
Optimization	Sequential Minimal Optimization [18,19]
Kernel	Polynomial Kernel (exponent: 1)
Hyperparameter c	1.0

Table 2. Parameters of Artificial Neural Network

Option / Parameter	Status / Value
Learning Rate	0.3
Momentum	0.2
Training	Back Propagation
Activation of Hidden Layer	Sigmoid
Activation of Output Layer	Linear
Number of Hidden Layers	1
Number of Neurons in Input Layer	4
Number of Neurons in Hidden Layer	3
Number of Neurons in Output Layer	1

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RESULTS AND DISCUSSION

Suitable Combination of Sensor Placement and Machine Learning Algorithm

Table 3 shows RMSE of ball velocity between the actual and predicted values. The results showed that the proposed method using M5P could predict ball velocity with smallest error in both sensor placement (RMSE < 2.0 mph). A tree-based model like M5P was also effective in previous research by Gomaz et al [4]. These results suggest that M5P is best algorithm for the proposed method. On the other hand, there was almost no difference between sensor placements. Thus, it is considered that both trunk and pelvis are allowed as sensor placement for a single inertial sensor of the proposed method. The Bland-Altman plot was used for the proposed method using pelvis inertial sensor and M5P algorithm.

Table 3. RMSE between the Actual and Predicted Ball Velocity

Inertial Sensor Placement	Algorithm	RMSE of Ball Velocity [mph]
Trunk (sternum)	Linear Regression	3.31
	SVM	3.42
	Gaussian Process	3.14
	ANN	3.48
	M5P	**1.89**
Pelvis	Linear Regression	3.61
	SVM	3.69
	Gaussian Process	3.27
	ANN	3.54
	M5P	**1.75**

Statistical Test and Bland-Altman plot

The results of t-test showed that there was no significant difference between the actual and predicted ball velocity. Table 4 and Figure 2 show the results of the Bland-Altman plot for the proposed method using pelvis inertial sensor and M5P algorithm. The results showed that LOA of the Bland-Altman plot included zero (Table 4 and Figure 2). These results indicate that there were no fixed errors in the proposed method. On the other hand, there was significant correlation between difference (vertical axis) and mean (horizontal axis) of the Bland-Altman plot (Table 4 and Figure 2). These results suggest that the proposed method has proportional error in the ball velocity prediction.

Table 4. Results of the Bland-Altman plot.

LOA of Difference in the Bland-Altman Plot [mph]	Correlation between Difference and Mean
-2.95 to 3.12 (Including zero)	r = 0.342 ($p < 0.05$)

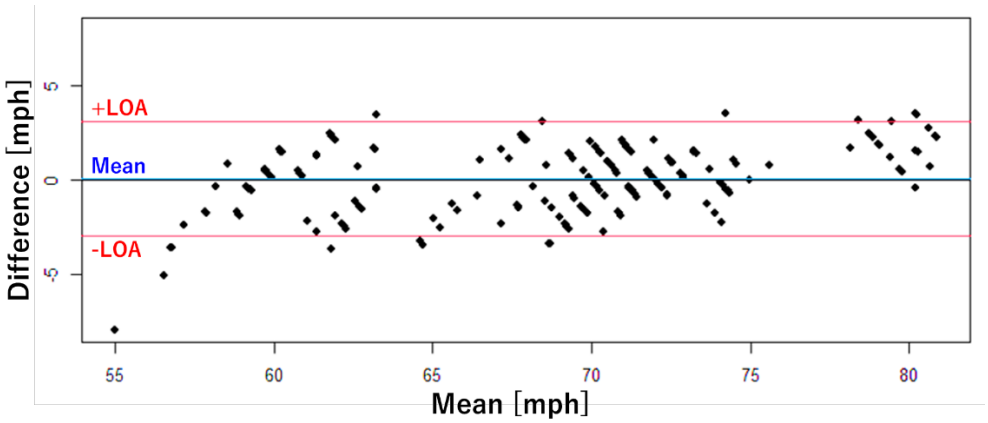


Figure 2. Bland-Altman Plot

Usefulness of Ball Velocity Prediction using a Single Inertial Sensor

The proposed method using suitable combination of sensor and algorithm could predicted ball velocity with 1,75 mph RMSE (Table 3). Furthermore, results of the Bland-Altman plot showed that there were no fixed errors in the proposed method (Table 4 and Figure 2). These results suggest possibility that the proposed method can be applied for ball velocity measurement using a single inertial sensor such as smartphone. The results of comparison for sensor placement showed that user can select either trunk or pelvis to put a single inertial sensor. This advantage will contribute usability and comfortability of the proposed method.

Limitations and Future Works

There was proportional error in the proposed method (Table 4 and Figure 2). Thus, modification methods to remove this proportional error should be developed. In addition, the prediction method was evaluated in only fastball pitch performed from young player. Thus, the prediction method should be evaluated for breaking ball and various players. Furthermore, future works should evaluate whether actual smartphone could be applied for the prediction method.

CONCLUSION

This study proposed the ball velocity prediction method using the only a single inertial sensor. The proposed method predicted ball velocity using by a single inertial sensor and machine learning technique. The prediction method was tested in Gomaz et al.'s public data. In addition, suitable sensor placement and machine learning algorithm were explored. The results of comparison for sensor placement showed that user can select either trunk or pelvis to put a single inertial sensor. Furthermore, the results showed that greatest algorithm (M5P) could accurately predict ball velocity by only single inertial sensor and body parameters (RMSE < 2.0 mph). Moreover, the Bland-Altman plot showed that there was no fixed error in the prediction method. These results suggest that ball velocity can be measured by only single inertial sensor.

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