

## Postprint of “Prediction of Vertical Ground Reaction Force (vGRF) during Volleyball Spike Landing Based on a GRA-BP Model”

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### Abstract

**Objective** To construct a coupled mathematical model based on grey relational analysis (GRA) and a BP neural network (BP neural network) to predict the vertical ground reaction force (vGRF) during spike landing in volleyball players, so as to replace a three-dimensional force platform. **Methods** Twenty second-level volleyball players from Beijing Sport University were recruited and performed volleyball spike actions using a two-step approach run-up. Kinematic and kinetic data were synchronously collected via a motion capture system and a three-dimensional force platform. OpenSim was used to compute the kinematic data of volleyball players during two-step run-up spike landings. GRA was adopted to filter out kinematic variables with a relational grade lower than 0.98. Root mean square error, mean absolute percentage error, mean absolute error, and R were used as evaluation indices of the GRA-BP model, and Kendall' s W coefficient was used to assess the consistency between the predicted vGRF and the measured vGRF. **Results** GRA results showed that 13 kinematic variables, including pelvic anterior-posterior tilt angle, pelvic lateral tilt angle, and pelvic rotation angle, had relational grades higher than 0.98. In the training set, the root mean square error between predicted and measured values was 0.271 BW, the mean absolute percentage error was 4%, the mean absolute error was 0.17 BW, and  $R = 0.999$ . In the validation set, the root mean square error between predicted and measured values was 0.235 BW, the mean absolute percentage error was 3.9%, the mean absolute error was 0.14 BW, and  $R = 0.998$ . In the test set, the root mean square error between predicted and measured values was 0.224 BW, the mean absolute percentage error was 3.6%, the mean absolute error was 0.14 BW, and  $R = 0.998$ . Kendall' s W coefficient was 0.945,  $P \leq 0.001$ . **Conclusion** The GRA-BP model established in this study can improve the accuracy of vGRF measurement during spike landing in volleyball players and shorten the measurement time.

## Full Text

### Abstract

**Objective:** To establish a coupled mathematical model combining Grey Relational Analysis (GRA) and Back Propagation (BP) neural networks for predicting the vertical ground reaction force (vGRF) during volleyball spike landings, thereby providing an economically feasible method for sports injury monitoring.

**Methods:** Twenty male volleyball athletes (age:  $21.2 \pm 1.4$  years, height:  $192.3 \pm 2.9$  cm, mass:  $83.5 \pm 2.6$  kg) from Beijing Sport University were recruited to perform spike actions using a two-step approach. Kinematic and kinetic data were synchronously collected using a motion capture system and three-dimensional force plates. OpenSim software was used to calculate the kinematic data during the two-step approach spike landing. GRA was employed to screen kinematic indicators, selecting those with correlation coefficients above 0.98 as input features for the BP neural network to replace the three-dimensional force plate. The dataset was randomly divided into training and test sets at a 4:1 ratio using the `cvpartition` function in MATLAB, with 20% of the training data reserved as a validation set.

**Results:** Thirteen kinematic features showed correlation coefficients exceeding 0.98, including pelvic anterior-posterior tilt angle, pelvic left-right tilt angle, and pelvic rotation angle. In the training set, the root mean square error (RMSE) between predicted and measured values was  $0.271 \pm 0.008$  BW, mean absolute percentage error (MAPE) was 3.9%, and mean absolute error (MAE) was  $0.17 \pm 0.0001$  BW, with  $R = 0.999$ . In the validation set, RMSE was  $0.235 \pm 0.0012$  BW, MAPE was 3.6%, and MAE was  $0.14 \pm 0.0001$  BW, with  $R = 0.998$ . In the test set, RMSE was  $0.224 \pm 0.0011$  BW, MAPE was 4.0%, and MAE was  $0.14 \pm 0.0001$  BW, with  $R = 0.998$ .

**Conclusion:** The GRA-BP model established in this study can significantly improve the accuracy of vGRF measurement during volleyball spike landings and shorten measurement time, providing a new pathway for coaches to obtain volleyball athletes' biomechanical data.

**Keywords:** vertical ground reaction force; grey relational analysis; neural network; volleyball spike; OpenSim

## 1 Introduction

Volleyball is one of the most popular sports worldwide. As a high-intensity jumping sport, volleyball players frequently perform takeoff and landing movements during training and competition. Research indicates that each player on the U.S. national volleyball team may perform 300-500 spike and block jumps during a single training session [1], with spikers showing higher jump frequencies than players in other positions [2]. The landing sequence and impact patterns in volleyball are closely related to lower limb stiffness during takeoff and landing

[3], making vertical ground reaction force (vGRF) a critical parameter in sports biomechanics analysis and clinical assessment [4]. vGRF serves as a decisive factor in volleyball-related injuries [5], with its magnitude, loading rate, and frequency characteristics all correlating with lower extremity injury risk. Excessive impact loads may lead to patellofemoral pain, anterior cruciate ligament injuries, and tibial stress fractures [6,18-20,36-37].

Despite the importance of vGRF, its measurement still faces technical bottlenecks. Although three-dimensional force plates can be used for fatigue monitoring and biomechanical analysis, their high installation costs and strict environmental requirements limit widespread application. Additionally, data collection is constrained as athletes must perform jumps or landings on the force plate, which may affect their natural movement patterns and reduce the ecological validity of the data [38]. Given these limitations, researchers have begun exploring machine learning methods to estimate vGRF using kinematic data.

Neural networks, with their powerful nonlinear dynamic processing capabilities and high fitting precision, have been widely applied in sports biomechanics research for predicting joint moments and dynamic parameters [7-8]. However, the nonlinear relationships between numerous kinematic factors affecting volleyball spike landings make traditional linear regression methods inadequate. Grey Relational Analysis (GRA) offers a quantitative method for evaluating the influence of multiple factors on outcomes, providing comprehensive decision-making basis without requiring large sample sizes and featuring simple computation processes [9]. GRA has been extensively used in engineering and medical fields [10-13], but its application in sports biomechanics remains relatively limited [10-13].

This study proposes an innovative approach by combining GRA with BP neural networks to identify key kinematic factors influencing vGRF during volleyball spike landings and improve prediction accuracy. This method not only enriches the application pathways of machine learning in sports biomechanics but also provides a new theoretical framework and empirical foundation for intelligent sports load modeling and assessment. The GRA-BP model can reduce dependence on force plates, improve data acquisition feasibility, and provide scientific support for injury prevention and training optimization in volleyball athletes.

## 2 Methods

### 2.1 Research Subjects

This study recruited twenty male volleyball athletes (age:  $21.2 \pm 1.4$  years, height:  $192.3 \pm 2.9$  cm, mass:  $83.5 \pm 2.6$  kg, training experience:  $8.8 \pm 2.3$  years) from Beijing Sport University. The study was approved by the Ethics Committee of Beijing Sport University (No. 2025124H).

## 2.2 Data Collection

The study focused on volleyball spike technique movements. Kinematic and kinetic data during spiking were collected using a Qualisys motion capture system and Kistler three-dimensional force plates (9281B, Kistler). Each subject performed spike actions using a two-step approach, with three successful trials collected per subject [8]. A key-frame extraction method was used to capture data at critical moments including takeoff and landing instants.

## 2.3 Data Processing

Experimental data collected by the Qualisys motion capture system were pre-processed using Qualisys Track Manager software and exported as .C3D format files [16]. Ground reaction force data were converted to .mot files, while marker trajectory data were converted to .trc files for subsequent analysis in MATLAB (2017b). OpenSim generic model (OpenSense\_{Subject}) was used to scale the model according to each subject's anatomical parameters to improve individualized fit [17-20].

Inverse kinematics (IK) was applied to minimize errors between experimentally measured marker trajectories and calculated model marker positions, thereby improving angle calculation accuracy [17-20]. Inverse dynamics (ID) was then performed using ground reaction force data and kinematic data to calculate joint moments and dynamic parameters, obtaining detailed biomechanical information during movement [21]. The calculated kinematic data were filtered using a built-in filter with a cutoff frequency of 10-20 Hz [23-24]. vGRF data were normalized by dividing by body weight:  $vGRF(N)/(mass(kg) \times gravitational\ acceleration(N/kg))$  [3].

The dataset was created from the processed kinematic and kinetic data of volleyball spike movements. In this study, the `cvpartition` function in MATLAB randomly divided the dataset into training and test sets at a 4:1 ratio, with 20% of the training data used as a validation set [22].

## 3 GRA-BP Model Development

### 3.1 Grey Relational Analysis

The fundamental principle of Grey Relational Analysis (GRA) is to evaluate the degree of association between data sequences based on the geometric proximity of curves in open data structures [9,12-13]. The analysis proceeded as follows:

**Data Preprocessing:** The study included 13 kinematic feature vectors and 1 kinetic feature vector (vGRF). The reference sequence (mother sequence) was defined as  $Y = Y(k)$ , where  $k = 1, 2, \dots, n$ , representing the vGRF data. Kinematic data served as comparative sequences (sub-sequences)  $\mathbf{X}_i = X_i(k)$ , where  $i = 1, 2, \dots, m$  and  $k = 1, 2, \dots, n$ . To eliminate dimensional effects, all data were

normalized:  $X_i(k) = \frac{X_i(k) - \bar{X}_i}{\sigma_i}$ , where  $\bar{X}_i$  is the mean and  $\sigma_i$  is the standard deviation.

**Correlation Coefficient Calculation:** The correlation coefficient between kinematic and kinetic data was calculated as:

$$\xi_i(k) = \frac{\min_i \min_k |Y(k) - X_i(k)| + \rho \max_i \max_k |Y(k) - X_i(k)|}{|Y(k) - X_i(k)| + \rho \max_i \max_k |Y(k) - X_i(k)|}$$

where  $\rho$  is the distinguishing coefficient (typically 0.5),  $\min_i \min_k |Y(k) - X_i(k)|$  is the two-level minimum difference, and  $\max_i \max_k |Y(k) - X_i(k)|$  is the two-level maximum difference.

**Grey Relational Degree:** The grey relational degree between  $Y$  and  $X_i$  was calculated as:

$$\gamma_i = \frac{1}{n} \sum_{k=1}^n \xi_i(k)$$

Based on the GRA results, kinematic features with correlation coefficients greater than 0.98 were selected as input vectors for the BP neural network. Thirteen key kinematic features were identified, including pelvic anterior-posterior tilt angle, pelvic left-right tilt angle, pelvic rotation angle, right hip flexion angle, right hip adduction angle, right hip rotation angle, right knee flexion angle, right knee adduction angle, right ankle dorsiflexion angle, left hip adduction angle, left knee flexion angle, left hip rotation angle, and left knee adduction angle.

### 3.2 BP Neural Network Structure

The BP neural network provides a nonlinear mapping from input to output [13,27-28]. Based on the selected 13 kinematic features with correlation coefficients above 0.98, the network topology was designed as follows:

**Input Layer:** The input layer contained 13 nodes corresponding to the selected kinematic features.

**Hidden Layer:** A single hidden layer was adopted, as theoretical work by Kolmogorov and empirical formulas demonstrate that a single hidden layer network can approximate any nonlinear function with arbitrary precision [15]. Through cross-validation, the optimal number of hidden nodes was determined to be 10-20, with 15 nodes selected for this model. The **Tansig** function was used as the activation function for the hidden layer.

**Output Layer:** The output layer contained a single node representing the predicted vGRF.

**Training Parameters:** The maximum number of training iterations was set to 1000, with a target minimum error of 0.0001. The learning rate  $\eta$  was set to an appropriate value to ensure stable convergence without excessive training time.

Figure 4

Figure 1: Figure 4

The network training process involved: 1. Forward propagation to calculate hidden layer outputs:  $H_j = f(\sum_{i=1}^{13} \omega_{ij} X_i + a_j)$  2. Calculation of predicted output:  $Y_i = f(\sum_{j=1}^l \omega_{jk} H_j + b_k)$  3. Error calculation:  $e_k = Y_m - Y_i$ , where  $Y_m$  is the measured value 4. Backpropagation to update weights:  $\omega_{ij} = \omega_{ij} + \eta H_j (1 - H_j) \omega_{jk} e_k$  and  $\omega_{jk} = \omega_{jk} + \eta H_j e^k$

### 3.3 GRA-BP Predictive Model

shows the schematic diagram of the GRA-BP predictive model. The model integrates grey relational analysis for feature selection with BP neural network for prediction, enabling accurate vGRF estimation from kinematic data while reducing data redundancy and improving computational efficiency.

## 4 Results and Analysis

### 4.1 GRA Results

The GRA identified 13 kinematic features with correlation coefficients exceeding 0.98. These features primarily encompass pelvic, hip, knee, and ankle motion parameters that describe posture changes, joint angle adjustments, and impact absorption mechanisms during volleyball spike landings. Pelvic motion plays a crucial role in lower limb biomechanics, determining trunk stability and influencing lower limb movement coordination [32]. Excessive pelvic rotation may increase hip and knee loading, affecting movement efficiency and injury risk [14,20,34]. Hip joints serve as the core hub of lower limb movement, with appropriate flexion angles helping to buffer impact forces [4,15,34]. The knee joint bears weight, absorbs shock, and stabilizes the lower limb, with larger flexion angles extending impact duration and reducing injury risk [8,20]. Ankle dorsiflexion is the first link in transmitting ground reaction forces to the lower limb, with proper dorsiflexion helping to buffer impact loads [28].

### 4.2 BP Neural Network Prediction Results

The GRA-BP model demonstrated excellent predictive performance across all datasets:

**Training Set:** RMSE =  $0.271 \pm 0.008$  BW, MAPE = 3.9%, MAE =  $0.17 \pm 0.0001$  BW, R = 0.999

**Validation Set:** RMSE =  $0.235 \pm 0.0012$  BW, MAPE = 3.6%, MAE =  $0.14 \pm 0.0001$  BW, R = 0.998

**Test Set:** RMSE =  $0.224 \pm 0.0011$  BW, MAPE = 4.0%, MAE =  $0.14 \pm 0.0001$  BW, R = 0.998

Figure 6

Figure 2: Figure 6

summarizes the model performance evaluation metrics. The high R-values ( $>0.998$ ) across all datasets indicate excellent fit and generalization capability.

illustrates the training results, showing that the model stopped training when validation error began to increase, demonstrating good training status without overfitting.

Compared to existing models including PCA-BP [29], WOUDA [28], PSO-GRA-BPNN [30], and PCA-WNN [4], the GRA-BP model showed superior accuracy with RMSE ranging from 0.224 to 0.271 BW, MAPE of 3.6-4.0%, and MAE of 0.14-0.17 BW. The model's use of the **Tansig** activation function, which outputs values in the range  $[-1,1]$ , provided better handling of both positive and negative inputs compared to **Sigmoid** functions used in other models, enabling faster learning and improved gradient descent.

### 4.3 Kendall's Coefficient of Concordance

Kendall's  $W$  coefficient was used to evaluate consistency between predicted and measured values. The results showed  $W = 0.945$  with progressive significance  $\$ \$0.001$ , indicating significant consistency between model predictions and actual measurements.

## 5 Discussion

vGRF is a core kinetic parameter in sports biomechanics analysis, widely used in injury risk assessment, rehabilitation program development, and performance optimization [4-5]. In high-intensity jumping sports like volleyball, athletes experience instantaneous high-impact loads during spike landings, with load magnitude, loading rate, and frequency characteristics all correlating with lower extremity injury risk [18-20,36-37].

Traditional force plate measurements, while providing high-precision data, have several limitations: (1) high equipment cost limits large-scale implementation; (2) strict installation requirements restrict application to actual sports venues; (3) data collection constraints may alter natural movement patterns and reduce ecological validity [38]. These limitations have prompted researchers to explore machine learning approaches for vGRF estimation.

Neural networks have demonstrated powerful nonlinear modeling capabilities in sports biomechanics [39]. Current research directions include: (1) regression models based on kinematic data [4], which use motion capture systems to obtain joint angles and statistical models for prediction, though with limited accuracy due to strong nonlinear relationships; (2) machine learning prediction methods

[8-10,38], where deep learning models like MLP and LSTM have achieved promising results; (3) data-driven models based on segmental accelerations and plantar pressure [21-22], which can accurately estimate vGRF in cyclic movements but struggle with complex patterns like cutting and landing.

This study's GRA-BP model integrates feature selection with predictive modeling, offering several advantages: (1) GRA quantifies correlations between kinematic variables and vGRF, optimizing neural network inputs and improving prediction accuracy [21-23]; (2) the model reduces dependence on force plates and improves data acquisition feasibility; (3) it provides scientific support for injury prevention and training optimization.

The model demonstrates strong potential for practical applications: (1) **Injury monitoring:** When predictions significantly exceed individual baseline values, the model can alert coaches to potential injury risks; (2) **Training optimization:** By analyzing trends across training cycles, the model enables individualized training load management and technical feedback; (3) **Rehabilitation:** The model can track recovery progress and assess readiness for return-to-sport by comparing post-rehabilitation predictions with baseline values.

However, the study has limitations: (1) The relatively homogeneous sample (similar height and body mass) may limit generalizability to broader populations; (2) Potential overfitting risks with small sample sizes, despite feature selection; (3) Model scaling based on static postures may introduce bias due to individual anatomical differences. Future research should expand dataset diversity, incorporate wearable sensor technologies (IMUs, plantar pressure sensors), and develop personalized parameter adjustment mechanisms for different populations.

## 6 Conclusion

This study developed a GRA-BP model that successfully predicts vGRF during volleyball spike landings with high accuracy. The model selected 13 key kinematic features with correlation coefficients exceeding 0.98, including pelvic tilt angles, hip angles, knee angles, and ankle angles. Prediction results showed high consistency with force plate measurements, with test set RMSE of  $0.224 \pm 0.0011$  BW, MAPE of 4.0%, MAE of  $0.14 \pm 0.0001$  BW, and  $R = 0.998$ .

The GRA-BP model provides coaches and sports scientists with a new pathway to obtain volleyball athletes' biomechanical data, reducing dependence on expensive equipment while improving data acquisition efficiency. The model offers valuable applications in injury prevention, training optimization, and rehabilitation monitoring.

Future research directions include: (1) expanding dataset diversity across different populations; (2) integrating wearable sensor technologies for real-time monitoring; (3) developing adaptive algorithms for general fitness applications; (4) implementing regularization techniques and transfer learning frameworks to

enhance model robustness; (5) creating explainable AI methods to visualize relationships between model outputs and biomechanical mechanisms.

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Figure 2

Figure 3: Figure 2

Figure 3

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[39] DE ARAUJO FARIA V, AZIMBAGIRAD M, VIANI ARRUDA J, et al. Prediction of radiation-related dental caries through PyRadiomics features and artificial neural network in panoramic radiography[J]. Journal of Digital Imaging, 2021, 34(5):1237-1248.

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## Figures

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Figure 5

Figure 5: Figure 5