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Full Paper

Development of a simple force prediction model and consistency assessment of knee movements in ten-pin bowling

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Abstract: The aim of this research is to use LabVIEW to help bowlers understand their joint movements, forces acting on their joints, and the consistency of their knee movements while competing in ten-pin bowling. Kinetic and kinematic data relating to the lower limbs were derived from bowlers' joint angles and the joint forces were calculated from the Euler angles using the inverse dynamics method with Newton-Euler equations. An artificial-neural-network (ANN)-based data-driven model for predicting knee forces using the Euler angles was developed. This approach allows for the collection of data in bowling alleys without the use of force plates. Correlation coefficients were computed after ANN training and all values exceeded 0.9. This result implies a strong correlation between the joint angles and forces. Furthermore, the predicted 3D forces (obtained from ANN simulations) and the measured forces (obtained from force plates via the inverse dynamics method) are strongly correlated. The agreement between the predicted and measured forces was evaluated by the coefficient of determination (R^2), which reflects the bowler's consistency and steadiness of the bowling motion at the knee. The R^2 value was beneficial in assessing the consistency of the bowling motion. An R^2 value close to 1 implies a more consistent sliding motion. This research enables the prediction of the forces on the knee during ten-pin bowling by ANN simulations using the measured knee angles. Consequently, coaches and bowlers can use the developed ANN model and the analysis module to improve bowling motion.

Keywords: ten-pin bowling, knee movement, LabVIEW, artificial neural network, physical education

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INTRODUCTION

Sports provide significant health benefits and contribute to quality of life. Ten-pin bowling is a popular international indoor sport that requires accuracy of movement, steadiness of motion, and adequate direction and use of force. Biomechanical information, such as joint angles and forces, would be useful for bowlers and their coaches to improve bowlers' movements and poses. A bowler's posture of action can be observed and improved by studying his or her biomechanics.

Ten-pin bowling requires great skill and stable motion by the bowler. Compared to unskilled bowlers, skilled bowlers have greater mental toughness and are more confident in both performing a technique and handling the equipment. Skilled bowlers rely less on luck and undertake higher levels of planning and evaluation [1-2]. Bowlers are prone to upper limb injuries, which generally occur in the hand and fingers because holding the heavy bowling ball requires the bowler to insert the thumb and two other fingers into three holes drilled in the ball. Such injuries can potentially harm tendons and ligaments [3]. Hence, most research on ten-pin bowling in recent years has focused on the upper limbs [4-6]. While bowling, the bowler should keep the lower limbs stable to avoid injury. The ability to slide the front foot consistently enables the bowler to have a predictable stable base from which to deliver the ball more accurately [7]. Lower limb injuries are related to the bowler's gait and stance while throwing the bowling ball. An improper gait and/or stance can cause adductor muscle strains, ankle sprains, knee ligament injuries and femoral shaft fractures [8]. Investigating the motion of the lower limbs during bowling produces results that could be used to reduce injury. Kinematic information taken from ten-pin bowlers can broaden coaches' knowledge to train their athletes more effectively [9]. The kinematic and kinetic variables (i.e. angle, foot position, velocity and force) for ten-pin bowling have been observed and studied [7, 9, 10].

Through kinematics calculations, the velocities of body segments and relevant movement parameters, such as joint angle, joint force and joint moment, can be calculated. Euler's equations [11] are commonly used to obtain kinematics data. Riley and Kerrigan [12] conducted an analysis of the hip, knee and ankle joints using acceleration and angular acceleration to analyse the patients' specific impairments in the lower limb joints. Because of advancements in the integration of cameras and computers, dynamic image analysis systems are available for the analysis of sport biomechanics. Chan et al. [13] used three-dimensional (3D) high-speed capture cameras to analyse the movement of baseball players and, using kinematics and kinetics calculations, compared the players' knee loading and hip position during the performance of different actions. Chu et al. [9] profiled the techniques of elite-level ten-pin bowlers in terms of position, joint angle and velocity. Stuelcken and Sinclair [10] provided normative data on the magnitude of the ground reaction forces experienced by elite bowlers upon front foot contact while bowling. However, earlier studies offered insufficient data for the complete construction of a systematic model, which requires numerous calculations. Few researchers have computed and processed the large amounts of data involved in kinematic and kinetic calculations. Using one software package is a better way to build a systematic model containing all of the necessary functions. This approach also makes it easier to display the results (as angles, forces and moments) with illustrations and to process quantities of kinematic and kinetic data.

In this study, combined calculation programmes were employed using the data acquisition programming function in LabVIEW (National Instruments). LabVIEW is a widely used graphical

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programming language that facilitates communication between laboratory equipment and a personal computer. LabVIEW systems are called virtual instruments [14-15]. Engineers use this software for short-term planning, development and applications because of its good adaptability and flexibility in terms of compatible tools, test design, measurements, control systems and analysis [16]. Virtual instrumentation in LabVIEW is hierarchical and modular, making it very useful for programme design. Riemann et al. [17] used LabVIEW to convert and sample vertical ground reaction force data from a force plate and to process the signal for data analysis. Gopalai et al. [18] regenerated and displayed the motion of a lawn bowler with the aid of physically attached, tri-axial wireless accelerometers on various body segments using data collected by LabVIEW virtual instrumentation. Hon et al. [19] used a wireless inertial sensor to analyse the arm swing of a ten-pin bowler and developed an interactive graphical user interface (GUI)-based LabVIEW programme to analyse and visualise the critical biomechanical parameters of the arm swing. However, these analysis systems were not able to verify the consistency of the bowling motion and lack biomechanical analyses of the lower limbs. In this study, LabVIEW was used to design a human-machine interface capable of displaying biomechanical information describing the lower limbs during ten-pin bowling.

Biomechanical parameters associated with the lower limbs while bowling, such as angles and forces, also affect the slide of the front foot. Thus, the relationships between these angles and forces must be derived and observed. Music et al. [20} constructed motion trajectories using a three-segment dynamic human body model (shank, thigh and HAT (head-arms-trunk)). The joint forces and moments were derived using a highly coupled system of differential equations. The Jacobian matrix (J) is a commonly used tool for describing human motion in 3D space [21-23]. Li et al. [21] stated that spherical coordinates and Euler angles can represent human motion and that the Jacobian matrix function can be used to calculate the dynamic equation for human motion. These studies indicate that joint angles and forces can describe 3D human motion and that the joint forces can be calculated from the joint angles using specific functions. Thus, it is possible to find and analyse the relationships between the joint angles and forces on the lower limbs during ten-pin bowling in this study.

Employing the analysis system in a bowling alley without the use of force plates and performing repeated testing would be very difficult. Therefore, in this study, the joint forces were estimated from the joint angles using artificial neural network (ANN) simulation. These simulation methods have been employed extensively in several fields. ANNs have been successfully and widely applied in the analysis of clinic biomechanics [24]. Barton and Lees [25] used an ANN to perform an automated diagnosis of gait patterns classified by hip-knee angles. A back-propagation neural network was used to carry out biomedical signal analysis [26-27]. Barton et al. [28] used an ANN to quantify the deviation of a patients' gait from a normal gait using kinetic and kinematic data. Uchiyama et al. [29] determined the static relationships between the elbow joint angle and the joint torque using an ANN technique in which integrated electromyograms and joint angles were the inputs and the torque was the output. Thus, in this study an ANN model was constructed for the prediction and simulation of joint forces using joint angles.

To reduce the time required for ANN simulation using a large data set and to facilitate observation of the bowling motion in the lower limbs, this study focuses on the knee joint for analysis.

When a bowler slides on a surface, more weight is placed on the sliding leg. For the duration of the horizontal movement during floor contact, sliding decreases the loading of the ankle joint and increases the loading of the knee joint [30]. The knee joint has a large impact on the lower limbs in terms of reactive stability control [31]. The conditions of the bowling motion can therefore be observed most easily in the knee joint. Additionally, changes in the bowling movement result in a greater range of motion for the knee joint than for other joints. Therefore, in this study, the knee is the main source of data for the evaluation and analysis of bowlers' lower-limb motion. Accuracy and consistency have been recognised as important factors in ten-pin bowling performance [7]. Razman et al. [7] indicated that the consistency of the side-to-side foot path at the start of the slide is important for successful bowling. The objective of this research is to develop an analysis model for a simple prediction of joint forces using the measured angles of the knee without using force plates, and to assess the consistency of the knee in ten-pin bowling.

MATERIALS AND METHODS

Participants

Eight bowlers from a Taiwanese ten-pin bowling club (age: 28.8 ± 6.9 years; height: 1.71 ± 0.05 m; weight: 77.5 ± 22.1 kg) voluntarily participated in the study. None of the participants had a history of lower-limb surgery, nor had they suffered any limb injuries during the three months prior to the study. All of the participants provided written consent to the experimental protocol, which was approved by the institutional review board.

Data Collection and Processing

Six high-speed infrared cameras were used to collect the trajectories of the reflective markers. A 3D motion analysis system (Vicon MX) with two AMTI force plates (type OR6-6, 1000 Hz) was used to record the motion of and the force applied by the participants' feet. Human body characteristics (the reflective markers' positions) were used to define the coordinate positions. The angular movement, angular velocity and angular acceleration of the joints were calculated using the markers' positions. Measurements of the ground reaction forces and moments were obtained from the force plates. Each participant was involved in 10-20 trials for analysis.

The laboratory coordinate system was used as the reference to describe the 3D motion. A rotation matrix was used to describe the rotation of an object, and the relative motion and rotation matrix represent any two segments of the human body [32-34]. The Euler angles were used to analyse the angular motion of the rotating joints (Eq. (1)). Figure 1 shows the 3D coordinate system

$$R_{Y-X-Z}(\alpha,\beta,\gamma)=\begin{bmatrix} R_{11} & R_{12} & R_{13} \\ R_{21} & R_{22} & R_{23} \\ R_{31} & R_{32} & R_{33} \end{bmatrix}=\begin{bmatrix} S\alpha S\beta S\gamma + C\alpha C\gamma & S\alpha S\beta C\gamma - C\alpha S\gamma & S\alpha C\beta \\ C\beta S\gamma & C\beta C\gamma & -S\beta \\ C\alpha S\beta S\gamma - S\alpha C\gamma & C\alpha S\beta C\gamma + S\alpha S\gamma & C\alpha C\beta \end{bmatrix} \quad (1)$$

where

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$$\beta = \tan^{-1}\left(-R_{23}, \sqrt{R_{13}^2 + R_{33}^2}\right),$$
$$\alpha = \tan^{-1}\left(R_{13}/C\beta,\ R_{33}/C\beta\right),$$
$$\gamma = \tan^{-1}\left(R_{21}/C\beta,\ R_{22}/C\beta\right),$$

S = sine, C = cosine, and $R_{Y\text{-}X\text{-}Z}$ is a rotation matrix for two segments of human body.

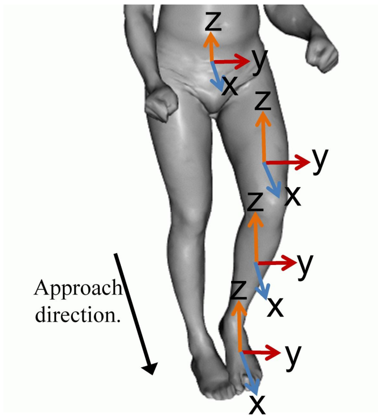

Figure 1. The coordinate system defined for the lower extremities

for every joint of the lower limb. The rotation angles about the y-axis (angle of flexion and extension), x-axis (angle of abduction and adduction) and z-axis (angle of internal and external rotations) are represented by α, β and γ respectively. The measurements taken from the plates were used to calculate the forces and moments of the joints of the lower limbs using the inverse dynamic method with the Newton-Euler equations (2 and 3) [35-37]:

$$\vec{F}_p = m\vec{a} - \vec{F}_d - m\vec{g} \tag{2}$$
$$\vec{M}_p = I\dot{\vec{\omega}} + \vec{\omega} \times I\vec{\omega} - \left(\vec{M}_d + \vec{r}_d \times \vec{F}_d + \vec{r}_p \times \vec{F}_p\right) \tag{3}$$

where m is the segment mass (kg); $\vec{a}$, the segment acceleration of the centre of mass (m/s^2); g, the acceleration due to gravity (m/s^2); $\vec{F}_p$, the proximal end joint force (N); $\vec{F}_d$, the distal end joint force (N); $\vec{M}_p$, the proximal end joint moment (N-m); $\vec{M}_d$, the distal end joint moment (N-m); I, the moment of inertia of the segment (kg/m^2); ω, the angular velocity of the segment (rad/s); $\vec{r}_d$, the distal end moment arm (m); and $\vec{r}_p$, the proximal end moment arm (m).

Derivation of Functions for Angles and Forces

The experimental data were collected from the bowlers in the laboratory. The bowling motion can be analysed using sport biomechanics, and the inverse dynamics method can be used to calculate the joint forces and moments from the ground reaction forces measured by force plates. However, force plates cannot be used in bowling alleys or during competitions. Instead, re-evaluating and predicting the forces or moments using an experimental database built from laboratory data is preferred. Thus, the Jacobian matrix function can represent the motion in ten-pin bowling as shown in Eq. (4) - Eq. (7) [21]:

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$$p_i(x,y,z)=\begin{bmatrix} f_1(\phi,\varphi) \\ f_2(\phi,\varphi) \\ f_3(\phi) \end{bmatrix}, \tag{4}$$

where p_i is the position vector of joint i, and φ and ϕ are compressed parameters representing the three Euler angles. In the spherical coordinate system, the matrix is expressed as

$$f_1(\phi,\varphi)=\sum_{j=1}^{n} r_j \cdot \sin(\phi_j)\cos(\varphi_j),$$

$$f_2(\phi,\varphi)=\sum_{j=1}^{n} r_j \cdot \sin(\phi_j)\cos(\varphi_j),$$

$$f_3(\phi)=\sum_{j=1}^{n} r_j \cos(\phi_j),$$

where r_j is the length of segment j.

$$\dot{p}_n = J\dot{\theta}_n \tag{5}$$

where θ_n is composed of all angles (from α, β and γ) for each joint, and

$$J=\left[\frac{\partial f_1(\phi,\varphi)}{\partial \phi_j}\;\frac{\partial f_1(\phi,\varphi)}{\partial \varphi_j},\frac{\partial f_2(\phi,\varphi)}{\partial \phi_j}\;\frac{\partial f_2(\phi,\varphi)}{\partial \varphi_j},\frac{\partial f_3(\phi)}{\partial \phi_j}\;\;0\right] \tag{6}$$

Using Newton's laws of motion, the equation can be expressed as

$$F = ma = m\cdot\frac{\partial v}{\partial t} = m\cdot\frac{\partial^2 P(x,y,z)}{\partial t^2} = m\cdot\frac{\partial (J\dot{\theta})}{\partial t}. \tag{7}$$

If the mass and length of the segments were to remain constant, the forces would be relative to only the angles. Thus, the relationships between the joint angles and forces on the lower limbs for bowling might be correlated. However, before the joint angles and forces can be analysed, the initial calculations require a computer software programme to process the large amount of data and to calculate the kinematics and kinetics. The functions for these calculations were combined using LabVIEW, and human-machine interface graphics were displayed using a multi-programme analysis. This approach is helpful for observing the phenomenon and the results of the ten-pin bowling motion.

Development of Graphical User Interface (GUI) Modular System

LabVIEW virtual instrumentation is useful in designing and planning an operating interface to analyse human motion in terms of kinematics and kinetics. In this study, the GUI modular analysis system for the lower limbs of bowlers engaged in ten-pin bowling was designed using LabVIEW (Figures 2 and 3). To import human parameters and experimental data, biomechanical descriptors such as joint angles and forces were calculated and displayed in the GUI panel. The biomechanical information describing each bowler was exported, saved and analysed using the system.

The developed GUI panel consists of three tabs: the bowler's information, motion analysis, and ANN analysis and application. In Figure 2, the bowler's information tab shows the bowler's basic information, usual bowling hand and support foot (whether the final step is taken with the left or right foot). The bowler's basic information includes sex, age, height, weight and years of

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experience in bowling. In the drawing in the middle of Figure 2, the bowler's usual bowling hand and support foot are shown in colour (right: red, left: blue).

The motion analysis tab, shown in Figure 3, imports the Vicon data (the bowler's height and weight), and the analysis system performs computations in terms of the kinematics and kinetics. The left side of the tab shows the original data acquired from the two force plates, the joint angles of the lower limbs (hip, knee and ankle), the joint forces and the joint moments. The right side of the tab displays the 3D dynamic motion of the lower limbs. The orientation of the 3D picture is adjustable, facilitating observation of the changes in the joint angles or motions.

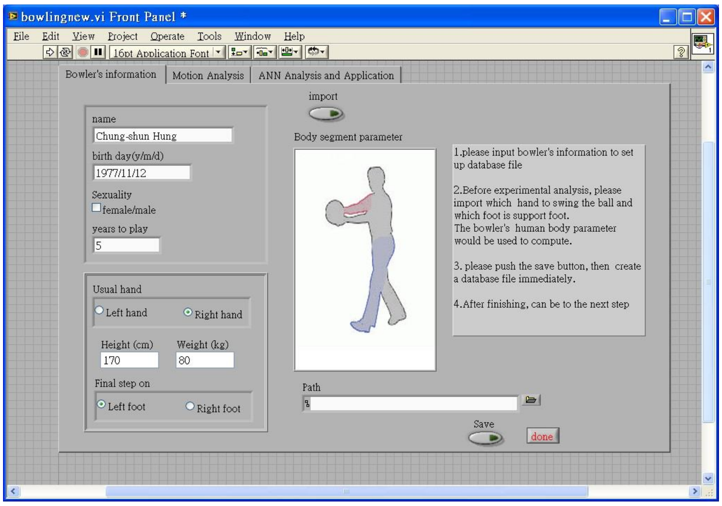

Figure 2. Bowler's information tab. The bowler's usual bowling hand and support foot are shown in colour (right: red, left: blue).

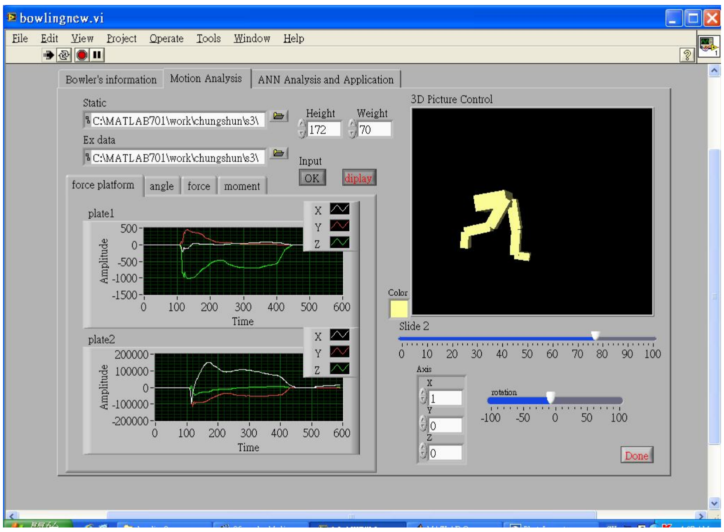

Figure 3. Motion analysis tab

In the ANN analysis and application tab, the joint angles and forces of each bowler's knee were exported from the motion analysis tab and simulated using an ANN model. To confirm and interpret the forces predicted from joint angles during the dynamic bowling motion, the system in this

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tab consists of LabVIEW with a developed three-layer network ANN model. Thus, coaches and bowlers can apply the ANN model for simple force prediction and assessment of knee position consistency during bowling.

ANN Model

The present study focused on the 3D Euler angles of the lower limb joints. Without force plates, the joint forces were estimated from the Euler angles. While bowling, the knee joint is likely to undergo motion. The accuracy and consistency of knee motion has a large impact on the lower limbs during bowling. An ANN model was constructed for each bowler, modelling the joints of the lower limbs based on the experimental data obtained in this study. The main aim of the study was to conduct trials and verify the simulated results relating to the movement of the knee joint, with a focus on performing a simple assessment of the knee-joint movements performed by bowlers and the consistency of those movements.

The joint forces are related to variations in the Euler angles through the transfer function (Eq. (7)) derived from the Jacobian matrix and differential equations. To enhance each bowler's unique transfer function, an ANN function capable of learning and training was created to replace the function in Eq. (7). The ANN architecture was constructed with one input layer, one hidden layer and one output layer to create a three-layer neural network. The ANN model of the knee consists of three neurons in the input layer, five neurons in the hidden layer, and three neurons in the output layer (Figure 4(a)). The Levenberg-Marquardt back propagation algorithm [38] was used for ANN training. A tangent sigmoid function was employed in both hidden layers and a linear transfer function was applied to the output layer. The model was trained using back propagation to predict the dynamic joint forces of the knee using the 3D Euler angles as the input data. Each participant was involved in 10-20 trials, each of which contributed 100-200 samples; thus, more than 1000 knee angles were available for use as input data for each bowler's ANN model. The ANN model was trained with back propagation using the opposing forces to the 3D joint forces of the knee (Fx, Fy and Fz versus the x-axis, y-axis and z-axis of the knee respectively). The ANN model would then be able to predict joint forces experienced in bowling alleys or in other situations without the use of force plates (Figure 4(b)).

Data Analysis and Consistency Assessment

The trend line for the relationship between the knee angles and the joint forces is found using linear regression on the sagittal plane. The weight and bias parameters for the network can be found after training the ANN model, and experimental data can be substituted into the network to simulate new results. If the correlation coefficient between the original measured forces and the simulated outputs is greater than 0.9 [39], then the transfer function relating joint angle and force in the ANN model can be built. The coefficient of determination (R^2) reflects the degree of fit or error for the ANN model of the knee while bowling and indicates the degree of convergence and accuracy of the simulation compared to the experimental data. The closeness of the R^2 value to 1 indicates the degree of success of the ANN model's simulation [40-41]. If the R^2 value is large, then the data used for training the ANN model converge easily. The R^2 value also reflects the precision of the

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experimental data and can therefore represent the consistency of the knee's bowling motion. If the R^2 value is small, then the data are divergent and the variation in the bowler's knee motion is large. Thus, the consistency and steadiness of a bowler's knee joints can be evaluated on the basis of the R^2 value, which is larger for bowlers with a higher degree of consistency.

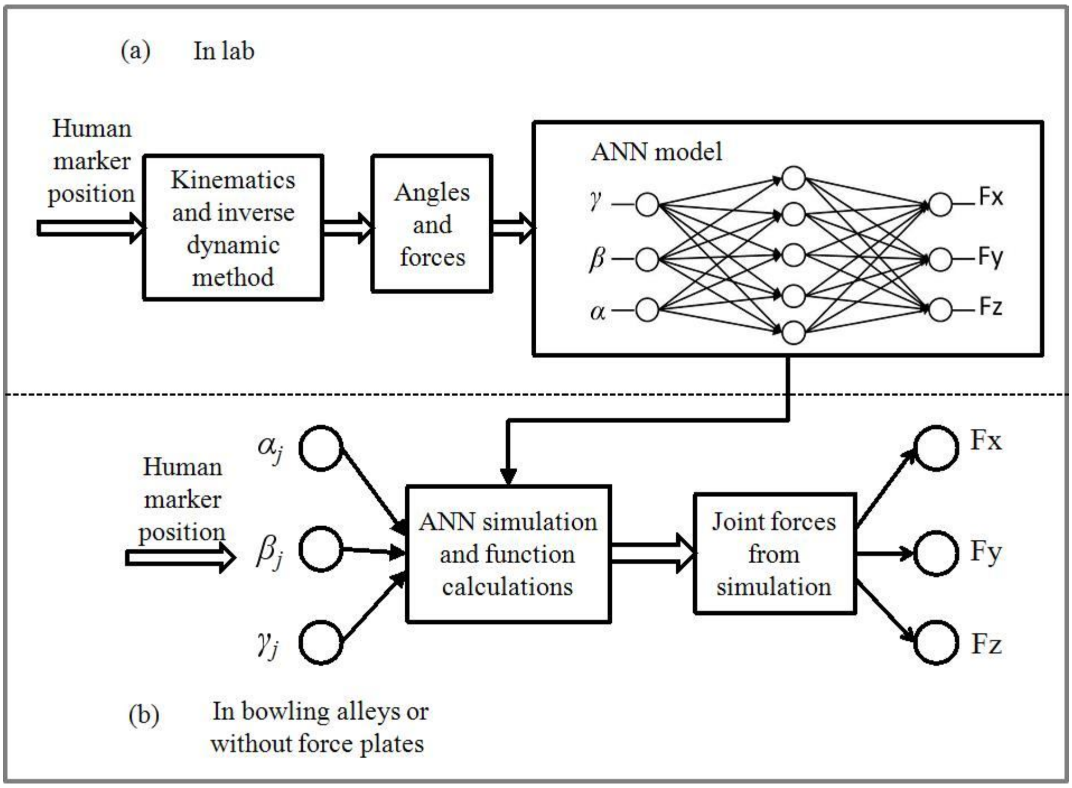

Figure 4. Structure of ANN model for prediction and simulation: (a) in laboratory – deriving the forces and angles used in ANN model from experimental data (α is rotation angle of flexion and extension versus Fz; β is rotation angle of abduction and adduction versus Fy; and γ is angle of internal and external rotation versus Fx); (b) in bowling alleys or without force plates – using ANN model obtained in laboratory with measured angles (α_j, β_j and γ_j) to predict joint forces.

RESULTS

Data on Angles and Forces

Bowlers need to possess great strength and speed to perform well in ten-pin bowling, but over-pursuing these requirements usually results in undetectable limb injuries. In the final step of the ten-pin bowling motion (Figure 5), the leg exerts extra force to allow the bowler to slide, thereby causing the bowler's body weight to be thrust in the forward direction.

The force plate signals were recorded starting when the support foot touches the plate and stopping at the end of the sliding motion (Figure 6(a)). The force plate data obtained from the bowling dynamic motion was used to analyse the sources of force. Then the data computed in terms of kinematics and kinetics was processed over the same range (e.g. the intercepting range of knee forces and angles shown in Figure 6). In Figure 6, the Fz on the knee decreased during the period ranging from touching the plate to stopping the slide.

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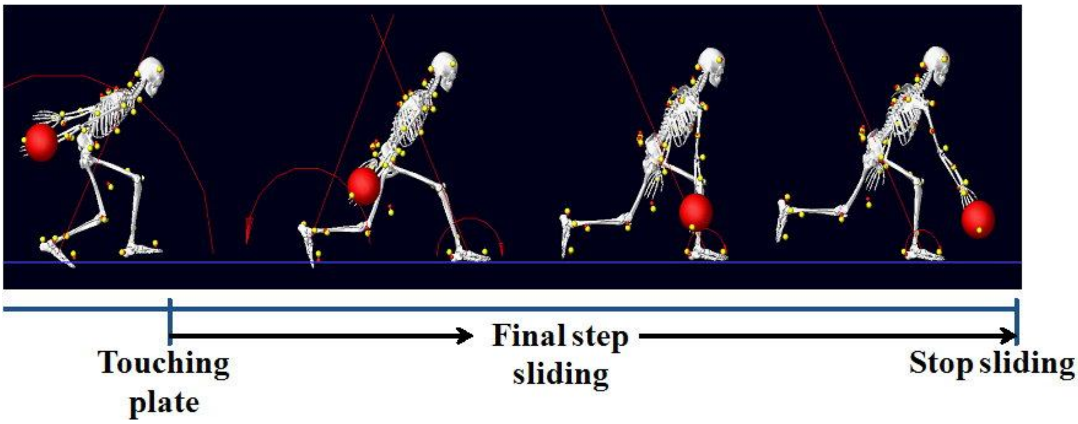
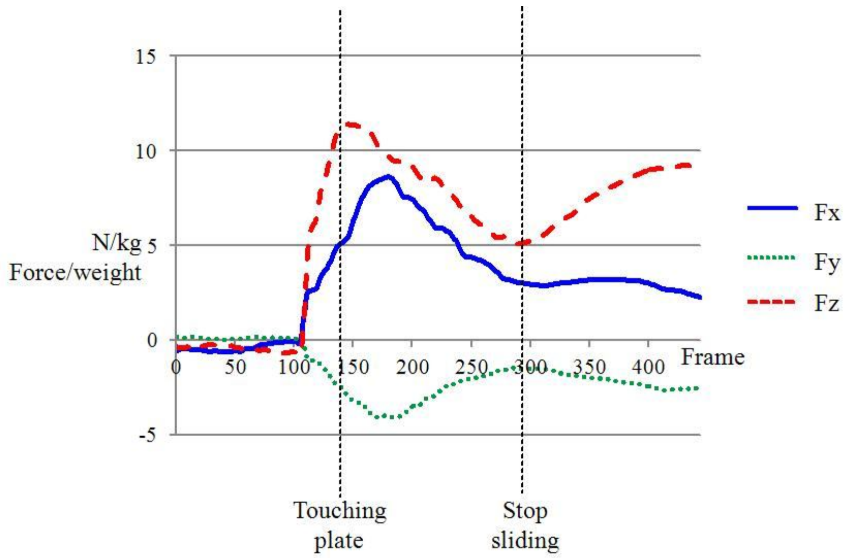
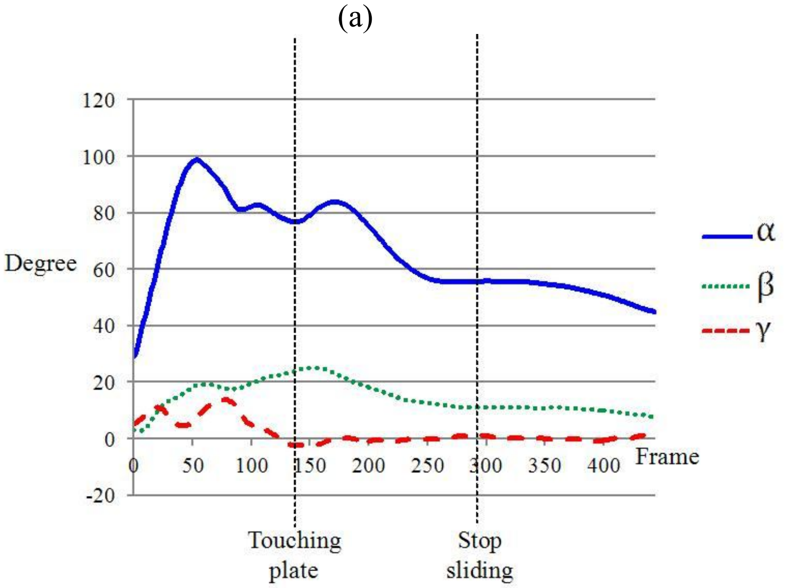


Figure 5. Illustration of the motions used during ten-pin bowling, created using LifeMOD™ (based on MSC.ADAMS®, Mechanical Dynamics Inc., USA) simulation



(a)



(b)

Figure 6. Determination of the fitted data range for the forces (a) and angles (b) of the knee joint

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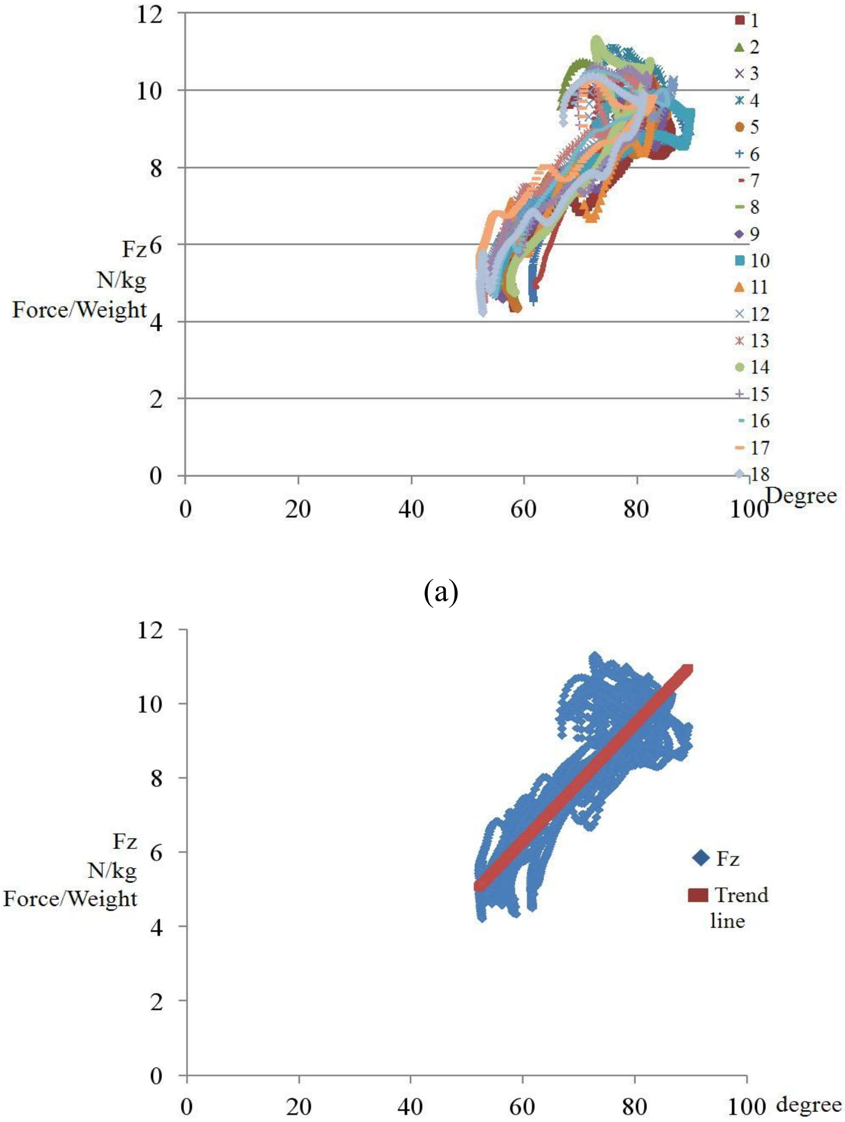
The angles and forces obtained from the processed data were exported to Microsoft Excel to construct distribution diagrams. Figure 7(a) shows the distribution of the knee angles during flexion under forces in the sagittal plane. The x-axis shows the knee angles (°), and the y-axis shows the vertical forces of the knee (N/kg). Figure 7(b) shows the distribution of data and the trend line obtained by a simple linear regression. The mean trend line slope for the eight bowlers is 0.14 N/kg-degree, which indicates that the vertical forces are positively correlated with the joint angles.



(b)

Figure 7. (a) Distribution of knee angles and forces during flexion (trial numbers: 1-18); (b) Regression of knee angles and forces during flexion

Analysis Using ANN Model

After the ANN model training, the correlation coefficients between the joint angles and forces were determined. The correlation coefficients between the original and simulated knee forces during

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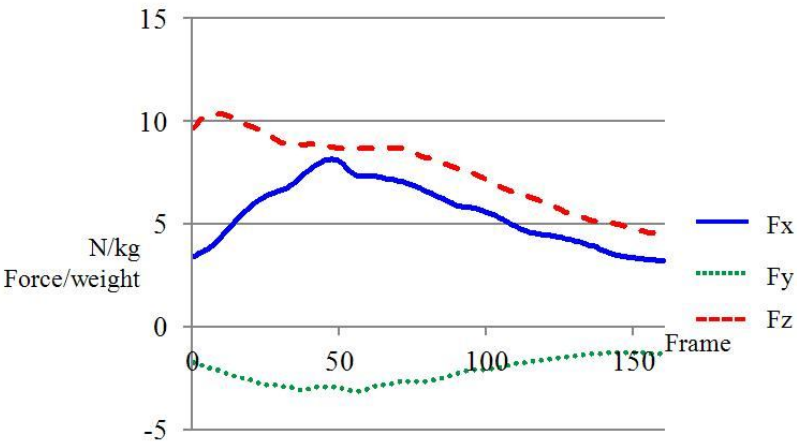
3D dynamic motion of eight bowlers obtained by the ANN model training are listed in Table 1. This approach can therefore be used to predict the forces on the knee joint of a competing bowler in competition. Figure 8 shows one of the subjects' changes in knee forces as predicted by the knee angles using the ANN model.

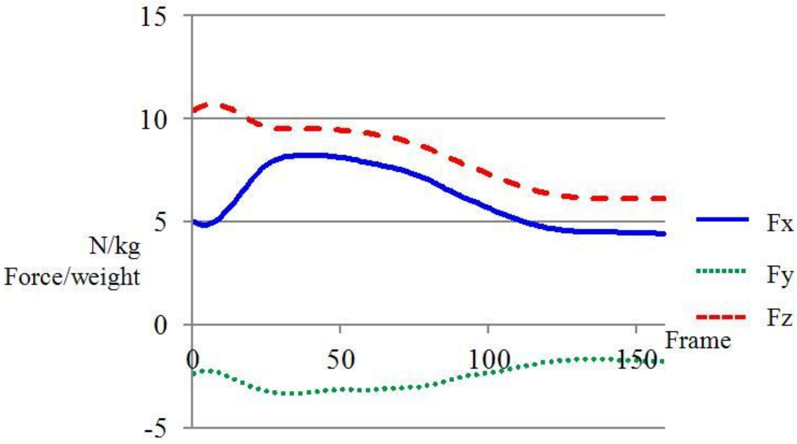
Table 1. Correlation coefficients between original and simulated knee forces for eight bowlers as determined by training the ANN model

r	S1	S2	S3	S4	S5	S6	S7	S8	Mean
r1	0.86	0.86	0.94	0.92	0.95	0.93	0.98	0.98	0.93
r2	0.93	0.88	0.91	0.81	0.92	0.87	0.96	0.91	0.90
r3	0.86	0.91	0.96	0.84	0.86	0.95	0.96	0.94	0.91

Note: r = correlation coefficient between original and simulated forces;
r1, r2 and r3 = correlation coefficients for Fx, Fy and Fz respectively;
S1-S8 denote bowlers number 1-8.



(a)



(b)

Figure 8. (a) Forces on the knee joint acquired from experimental data obtained with force plates, as determined by the inverse dynamics method; (b) The knee forces predicted from the knee angles using ANN simulation model.

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The forces predicted by the model were compared to the original forces for the new data sets to determine whether the R^2 values agreed [42]. Table 2 lists the R^2 values for the knee consistency assessment of the eight participants in the study.

Table 2. Validation of ANN model and consistency assessment using ANN

R^2	S1	S2	S3	S4	S5	S6	S7	S8
$(R1)^2$	0.86	0.73	0.89	0.84	0.89	0.87	0.97	0.96
$(R2)^2$	0.86	0.77	0.83	0.65	0.85	0.76	0.93	0.83
$(R3)^2$	0.74	0.82	0.92	0.71	0.74	0.91	0.92	0.88

Note: The coefficient of determination (R^2) reflects the degree of fit between the ANN model and the experimental data. $(R1)^2$, $(R2)^2$, and $(R3)^2$ were used to assess the consistency of Fx, Fy and Fz respectively. S1-S8 denote bowlers number 1-8.

DISCUSSION

Of the knee forces along the x-, y-, and z-axes, the vertical force Fz is greater than the forces in the other directions (shown in Figure 6). At this moment, a large amount of weight is placed on the sliding leg, which must be able to withstand the majority of the bowler's body weight and bear the force loading and the speed. A high lateral force Fy would adversely affect the consistency of the knee during bowling. The change in the range of motion of the ankle joint is relatively small, but this change imposes a burden on the knee in flexion and causes pain. An increase in the burden on the knee joint may result in injuries and inflammation. Patellar tendinitis of the knee is often induced by inflammation of the tendon between the patella and the shinbone. Bowling on a wooden sliding surface during floor contact may decrease the loading of the ankle joint but increase the load on the knee joint [30]. During the slide, the angle α of the knee decreased and the knee extended during the motion from touching the plate to stopping the slide (Figure 6). In similar sports such as cricket bowling, the vertical ground reaction forces are greater than the horizontal forces and fast bowlers use an extended knee during the front-foot contact phase [10, 43]. Therefore, a bowler must pay attention to his or her knee motion while moving the lower limbs during ten-pin bowling.

As the bowlers' legs slided on the plate, the range of knee angles was from 50° to 90° for flexion in the sagittal plane and the range of the vertical force Fz was approximately 4-12 N/kg (Figure 7). Linear regression was used to analyse the distribution of the angles and forces, and the mean slope of the trend line was 0.14 (Figure 7(b)). Thus, as the knee angles increased during flexion while bowling, the joint forces increased as well. Suter and Herzog [44], through EMG measurements, noticed that the muscle torque increased with increasing knee angles. Smith et al. [45] determined the joint angles and axial-joint contact forces during stair climbing and squatting activities. They found that an increase in the knee angles during flexion in the sagittal plane caused an increase in the axial tibio-femoral joint contact forces. These two studies illustrate that the forces on the knee joint increase with increasing knee angle. The results of our study agree with these previously reported results.

The motion of the bowler's knee was described by the individual transfer function obtained from the ANN model. Table 1 lists the correlation coefficients between the experimental and ANN model simulated knee forces. The means of the correlation coefficients for the eight bowlers are: r1 = 0.93, r2 = 0.9 and r3 = 0.91 for Fx, Fy and Fz respectively. All the means of the correlation coefficients are greater than 0.9. Additionally, the correlation coefficient for bowler 7 (S7) is the highest. On the basis of this validation of the ANN model, the joint forces can be predicted and the angles and forces can be interpreted as having a high correlation with and influence on the consistency of the knee. Force plates cannot be used in bowling alleys or during competitions; thus, the use of the ANN model is a good option. Changes in motion can be determined from the 3D knee forces predicted from the knee angle inputs into the ANN simulation model. Figure 8 shows one of the subjects' knee forces predicted using the ANN simulation model with the knee angles as input. The knee forces computed from the measured data and the 3D knee forces predicted by the ANN model are in good agreement. Therefore, the knee forces of the sliding leg during a ten-pin bowling competition can be predicted without the use of force plates.

In Table 2, a higher R^2 value implies greater accuracy and consistency of a bowler's knee joint. The R^2 values for the knee joint of bowler 7 (S7) from the ANN model are 0.97 in Fx, 0.93 in Fy and 0.91 in Fz. The consistency of the knee movement of bowler 7 is greater than that of the other bowlers. The R^2 values of bowler 4 (S4) are 0.84 in Fx, 0.65 in Fy and 0.71 in Fz, indicating that the knee's consistency is low and that the experimental data for the bowler are divergent. The R^2 values for the lateral and vertical forces for bowler 4 (S4) are even lower, implying unsteadiness, and these low values affect knee abduction/adduction and flexion/extension respectively.

The accuracy and consistency of knee movement is an important factor for assessing bowling performance and conditions. The R^2 value, which is calculated from the results of the ANN model, indicates the degree of convergence and accuracy of the simulation in comparison to experimental data. Because force plates cannot be used in bowling alleys or competitions, the R^2 value is an effective metric for assessing the level of consistency and steadiness of the knee during ten-pin bowling. This value provides bowlers and coaches with useful information for observing and analysing the bowling motion.

LabVIEW was used to construct a model for simple force prediction and consistency assessment of the knee during ten-pin bowling. The model was developed to collect and process data, filter signals and perform computations of the kinetics and kinematics. The angles, forces and moments of the lower-limb joints (hip, knee and ankle) could also be viewed with corresponding diagrams. The developed analysis module is simple to operate and gives bowlers the opportunity to view their joint conditions and motions during bowling. An individual ANN model incorporated into the LabVIEW model could be used to predict knee forces using measured knee angles for each bowler without the use of force plates. Coaches and bowlers can thus assess the consistency of knee motion with the R^2 values displayed in the analysis module on the GUI panel and can review and analyse the bowling motion to enhance performance.

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CONCLUSIONS

An analysis module and software with a GUI interface in LabVIEW for consistency assessment of the knee during bowling has been developed. The module processes signals from high-speed cameras and force plates, computes the kinetics and kinematics, generates a 3D diagram of the lower limbs, executes the learning and simulation algorithms for the ANN model, and performs a consistency assessment. The developed module is suitable for use in bowling alleys or during competitions where force plates are not practical. It is useful and easy to operate, enabling bowlers to study their knee motions while bowling and, consequently, to improve their consistency for better bowling performance.

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