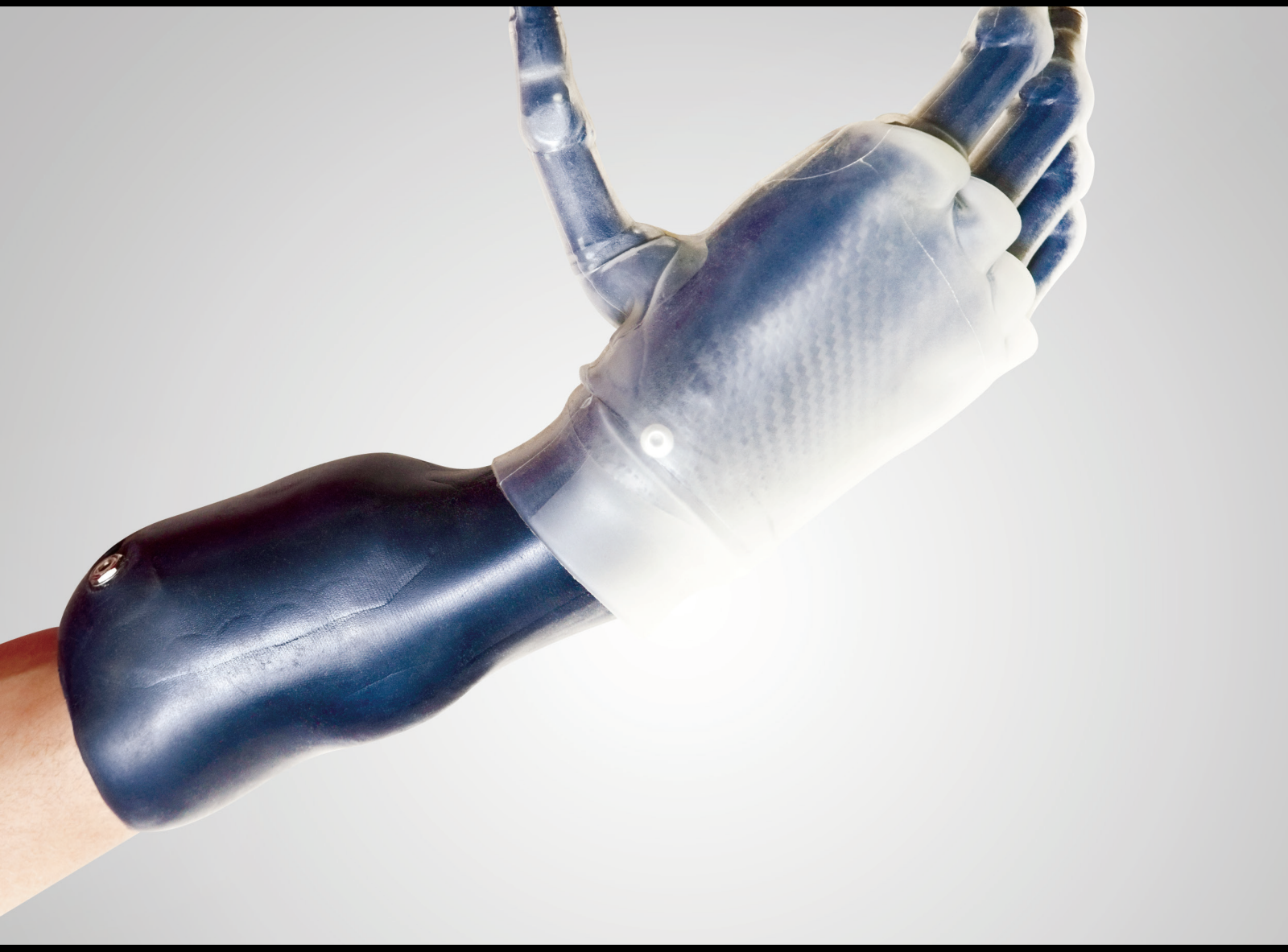
Applied Bionics and Biomechanics

Integrating Wearable and AI Techniques to Predict and Prevent Musculoskeletal Injury and Assist Rehabilitation

Lead Guest Editor: Qichang Mei
Guest Editors: Limimg Shu and Xianyi Zhang



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Applied Bionics and Biomechanics
Volume 2022, Article ID 3917566, 7 pages
https://doi.org/10.1155/2022/3917566

Research Article

The Use of Orthostatic Device for 90 Minutes Does Not Change Cardiovascular and Biomechanical Parameters of Patients with Spinal Cord Injury

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Received 28 April 2022; Revised 31 July 2022; Accepted 25 August 2022; Published 16 September 2022

Academic Editor: Xianyi Zhang

Background. Changes in autonomic function are often caused by spinal cord injuries, which lead to limited orthostatic positioning in these patients. *Objective*. To investigate the cardiovascular and biomechanical parameters during 90 min of postural elevation equipment usage comparing spinal cord injury and healthy subjects. *Methods*. A device was used that allowed patients with spinal cord injuries to remain in an orthostatic posture for 90 min. During this period, the physiological parameters were measured every 15 min. Cardiovascular parameters (heart rate, oxygen saturation, blood pressure, and autonomic nervous system) and biomechanical parameters of the plantar pressure distribution were evaluated. For blood pressure, heart rate, oxygen saturation, and autonomic nervous system, a two-way analysis of variance was applied. The mixed-effect model was applied to plantar pressure. The significance level was set at $p < 0.05$ for all statistical analyses. *Results*. No differences were observed between the groups in systolic blood pressure ($F = 0.07$), diastolic blood pressure ($F = 0.14$), heart rate ($F = 0.56$), and oxygen saturation ($F = 0.23$) at any of the time intervals throughout the experiment ($p > 0.05$). No statistical difference was observed in the mean plantar pressure values between the groups ($p = 0.35$) during the period in which they remained in the orthostatic position. *Conclusion*. The present study showed the absence of differences between spinal cord injury patients and control participants using the orthostatic device in terms of cardiovascular and biomechanical parameters over 90 min.

1. Introduction

Spinal cord injury (SCI) can affect the social participation of individuals, as it leads to motor changes such as paralysis, musculoskeletal injuries, pain, and osteoporosis [1]. Individuals with SCI need medical care and rehabilitation, which involve access to wheelchair-friendly environments and appropriate homecare equipment, transport, employment, and financial support [1]. Individuals with limited mobility show limited participation in social and community activities and are associated with the severity of depressive symptoms [2–4].

Another factor that contributes to limiting the return of patients with SCI to social and work contexts is the presence of postural hypotension. SCI leads to peripheral and central cardiovascular adaptations such as increased peripheral vascular resistance, reduced capillarization, and decreased artery diameters, which cause static hypotension and limits a standing position [5]. Orthostatic hypotension affects patients with

(a) (b) (c)

Figure 1: (a) Trunk bands; (b) leg bands; (c): side view—stand position.

SCI and is defined as a decrease in systolic blood pressure (BP) >20 mmHg or diastolic BP > 10 mmHg within three minutes of becoming an upright posture [6]. Changes in autonomic function are often caused by spinal sympathetic control, influencing BP stability, including hypotension during rest and severe drops in BP during orthostatic positioning [7]. Considering these alterations, patients with SCI remain in the orthostatic position for a maximum of 15 minutes without alterations in BP or the presence of postural hypotension [8–10]. Changes in BP can also lead to lower limb involvement, such as edema, which is reported in approximately 45% of patients with SCI, resulting in limited joint mobility and range of motion and an increased risk of thromboembolism [11]. Therefore, it is important to measure the plantar pressure during long-term orthostatic positioning in patients with SCI. Orthopedic and functional orthoses and exoskeletons are often used to support and minimize physical limitations [11]. Additionally, they can be defined as external mechanical structures that are wearable and capable of providing support to the affected body segments of disabled people [12, 13]. This can increase the autonomy in movements, which can be positively explored in the job market, especially in the industrial field [11–13]. The use of exoskeletons for people with disabilities began in the 60 s. However, the equipment used in health and rehabilitation is limited owing to the complexity of use [12], difficulties in reproducing the prototypes, and limitations of clinical trials to validate their effectiveness for vulnerable populations [12, 13]. To the best of our knowledge, this is the first study to evaluate the physiological and biomechanical parameters of subjects with SCI in an orthostatic position over a long period. Therefore, more studies are needed to highlight the risks and benefits of using postural elevation equipment for an extended period to help include device use in the laboral context of SCI patients. This study aimed to investigate cardiovascular and biomechanical parameters during 90 min of use of postural elevation equipment in healthy and SCI subjects.

2. Methods

2.1. Description of the Research Subjects. This cross-sectional experimental study was approved by the Local Committee of Ethics in Research (number CAAE 07192819.6.0000.5038). Due to the nature of the injury condition, a priori sample calculation was not performed. Thus, the participants were intentionally selected for the study.

The following individuals were included in the control and SCI groups: individuals between 18 and 50 years, with a height between 1.55 and 1.75 meters, a maximum weight of 100 kg, of both sexes, healthy, without associated vascular pathologies (disorders of the coagulation, decompensated diabetes, etc.), and with stabilized BP. Those with any serious cognitive/psychological impairment that could interfere with test performance, such as panic syndrome, major depression or anxiety attacks, and any relevant speech impairment that could impede their communication during the tests.

Participants without motor changes were included in the control group. In the SCI group, subjects with medium and lower lesions due to trauma, accidents, gunshot, and others, without associated vascular pathologies (clotting disorders, decompensated diabetes, etc.), with stabilized BP.

2.2. Description of the Equipment. The equipment (Figure 1(a)) was developed with AISI 409 stainless steel tubes, 28 mm in diameter and 0.7 mm thick joints, and articulated connections (Figure 1(b)). The participants were positioned in the orthostatic device and stabilized using adjustable straps on the shoulders, trunk, and hips. A wider Velcro band was added in the region of the legs (above the knee) and tibialis anterior. These

Table 1: Clinical and demographic characteristics.

	Control ($n = 15$)		Spinal cord injury ($n = 15$)		p value
Sex (male) (n)	7		11		
	Mean	(SD)	Mean	(SD)	
Age (years)	26.20	(7.25)	31.33	(8.42)	0.08
Weight (kg)	71.47	(15.5)	64.73	(14.35)	0.22
Height (m)	1.66	(0.10)	1.67	(0.08)	0.93
BMI (kg/cm^2)	25.61	(3.59)	23.25	(3.87)	0.09
Sleep quality (0–10)	6.70	(2.58)	8.23	(1.16)	0.06

Abbreviations: kg: kilogram; m: meters; SD: standard deviation; BMI: Body Mass Index.

bands allow greater stability of the lower limbs in the standing posture. Once positioned, the device was elevated, allowing the participant to remain standing. Similar to other wheelchairs, they can do this using a joystick. While elevated, users can still use the joystick to make fine personal adjustments to search for a more comfortable position. When the user is ready to leave the standing position, she presses the button and keeps it pressed until the device returns to its sitting position and can be used again as a regular motorized wheelchair. At the base of the equipment, a mechanism was installed that allowed ankle dorsiflexion movement to generate joint mobility during the orthostatic position (circulatory support) (Figure 1(c)).

2.3. Data Collection and Description. The participants were recruited for convenience, and a self-report sleep quality questionnaire and demographic characteristics were collected. The weight of each participant was then checked on a digital scale, and the first measurement of the autonomic nervous system activity in the sitting position was performed. Those to be evaluated were then positioned in the exoskeleton and fixed with belts specifically designed to guarantee user safety. After positioning each subject, they were placed in a condition of elevation with the exoskeleton (standing up position wearing the equipment) and maintained for 90 min. In this condition, the participants performed a battery of tests, which consisted of analysis of their heart rate, oxygen saturation, BP every 15 min, quantification of the activity of the autonomic nervous system, weight distribution on the equipment, and distribution of the plantar pressure on the baropodometry equipment every 30 min. Then, the users were removed from the elevated condition and returned to the sitting position, and the test was finished. Sleep quality data were collected to verify whether patients had any changes since vagal modulation is observed during sleep and sympathetic control is predominant during rapid eye movement (REM) sleep [14].

2.4. Cardiovascular Parameters. The participants' cardiovascular parameters (BP, heart rate, and oximetry) were inspected nine times at intervals of 15 min during and after the intervention. BP was assessed using a manual sphygmomanometer (BIC Brand™) that was properly calibrated and validated [13]. The cuff had a Velcro for fixation and a device that allowed the equipment to be inflated, which was positioned in the proximal region of the arm of the participants. The oximeter (BIC Brand™) was positioned on the finger, and oxyhemoglobin and deoxyhemoglobin were measured by red and infrared light [15]. The autonomic nervous system was evaluated using the InnerBalance(TM) at baseline, 30 min, 60 min, and 90 min of equipment use. The measurement of neurocardiac function reflects the dynamics of the autonomic nervous system (ANS), with measurements of the oscillations of the R–R intervals. EmWave(TM) software (Quantum Intech, Inc. Boulder Creek, CA, USA) was designed by the Institute of Heart Math. Data were processed using Kubios HRV(TM) version 2.1. The parameters analyzed were the sympathetic nervous system index (SNS) and parasympathetic nervous system index (PNS) were analyzed [16, 17].

2.5. Biomechanical Parameters. Before baropodometry, the subjects were weighed using a Renpho (TM) digital scale. Plantar pressure mean analysis was performed using a baropodometer (T-Plate, Medicapteurs (TM), France). Data of the plantar pressure mean they were collected for 50 s at four different moments during the period when the subjects were in the elevated position: one at Time 0, the second at 30 min, the third at 60 min, and the last at 90 min [18, 19].

2.6. Data Analysis. Data were analyzed using the statistical software GraphPad Prism 8.0. For the variables age, height, and body mass index, Student's t-test for Independent Samples was used. Data on weight and sleep quality showed a non-normal distribution, which is why they were evaluated using the Mann–Whitney U test. The groups were compared at the respective times (baseline, 15, 45, 60, 75, and 90 min), and the Shapiro-Wilk normality test was used. For BP, heart rate, oxygen saturation, and ANS, a two-way analysis of variance (ANOVA) was applied. The mixed-effect model was applied to plantar pressure. The significance level was set at $p < 0.05$ for all statistical analyses. Data are expressed as the mean (SD).

3. Results

3.1. Sample Characterization. The group samples had similar characteristics at baseline. No statistically significant differences were observed (Table 1).

3.2. Cardiovascular Parameters. No differences were observed between the groups in systolic blood pressure ($F = 0.07$), diastolic blood pressure ($F = 0.14$), heart rate ($F = 0.56$), and oxygen saturation ($F = 0.23$) at any of the

Table 2: Comparison of cardiovascular parameters over 90 min of maintaining the orthostatic position.

	Control ($n = 15$) Mean (SD)	Spinal cord injury ($n = 15$) Mean (SD)	p value	Mean difference (95% CI)
Systolic arterial pressure (mmHg)				
Time 0	118.0 (10.1)	117.3 (13.3)	>0.99	−0.667 (−13.26 to 11.93)
Time 15 minutes	116.7 (11.7)	114.8(15.4)	0.99	−1.867 (−16.47 to 12.74)
Time 30 minutes	114.7 (13.0)	115.3 (16.4)	>0.99	0.667 (−15.05 to 16.38)
Time 45 minutes	117.3 (13)	114.7 (19.2)	0.99	−2.667 (−20.32 to 14.98)
Time 60 minutes	116.7 (9.7)	114.7 (18.4)	0.99	−2.000 (−18.00 to 14.00)
Time 75 minutes	116.7 (12.3)	115.3 (17.6)	>0.99	−1.333 (−17.59 to 14.92)
Time 90 minutes	116.0 (11.8)	115.0 (17.8)	>0.99	−1.000 (−17.18 to 15.18)
Diastolic arterial pressure (mmHg)				
Time 0	76.7 (10.5)	79.3 (9.6)	0.98	2.667 (−7.95 to 13.29)
Time 15 minutes	78.0 (10.8)	79.3 (12.8)	>0.99	1.333 (−11.22 to 13.88)
Time 30 minutes	74.7 (9.1)	80.0 (13.1)	0.8	5.333 (−6.712 to 17.38)
Time 45 minutes	78.3 (9.6)	78.7 (14.6)	>0.99	−0.667 (−13.87 to 12.53)
Time 60 minutes	79.3 (8.0)	78.7 (15.5)	>0.99	−0.667 (−14.06 to 12.73)
Time 75 minutes	78.0 (9.4)	80.0 (16.0)	0.99	2.000 (−12.15 to 16.15)
Time 90 minutes	78.0 (10.1)	78.7 (15.0)	>0.99	0.667 (−13.05 to 14.38)
Heart rate (bpm)				
Time 0	86.6 (22.4)	91.7 (19.3)	0.99	5.067 (−17.10 to 27.24)
Time 15 minutes	85.9 (12.9)	94.8 (15.7)	0.52	8.933 (−6.349 to 24.22)
Time 30 minutes	85.9 (16.1)	86.9 (17.6)	>0.99	0.9333 (−16.92 to 18.78)
Time 45 minutes	87.9 (14.0)	91.6 (19.4)	0.99	3.667 (−14.31 to 21.65)
Time 60 minutes	81.7 (9.9)	89.7 (15.8)	0.55	8.000 (−6.149 to 22.15)
Time 75 minutes	86.6 (13.2)	87.8 (15.7)	>0.99	1.200 (−14.10 to 16.50)
Time 90 minutes	87.1 (14.7)	84.6 (15.0)	0.99	−2.533 (−18.16 to 13.09)
Oxygen saturation (%)				
Time 0	96.9 (1.6)	97.1 (1.5)	0.99	0.267 (−1.422 to 1.955)
Time 15 minutes	96.7 (2.7)	96.8 (1.7)	>0.99	0.067 (−2.309 to 2.442)
Time 30 minutes	96.7 (1.9)	97.3 (1.3)	0.93	0.600 (−1.159 to 2.359)
Time 45 minutes	96.9 (1.5)	96.9 (2.5)	>0.99	0.000 (−2.261 to 2.261)
Time 60 minutes	96. (2.8)	97.4 (1.6)	0.89	0.933 (−1.505 to 3.372)
Time 75 minutes	97.0 (1.6)	96.9 (1.7)	>0.99	−0.067 (−1.863 to 1.730)
Time 90 minutes	97.7 (1.0)	97.1 (1.8)	0.93	−0.533 (−2.096 to 1.029)

SD = standard deviation; 95% CI = 95% of CI.

time intervals throughout the experiment ($p > 0.05$) (Table 2). This could characterize the average clinical stability in the cardiovascular functions during the use of the exoskeletal postural elevation, with regard to the systolic and diastolic BP (with the mean below or until 120/80 mmHg), maximum heart rate (below 100 bpm), and oxygen saturation (above 95%).

3.3. Biomechanical Parameters. Figure 2 shows the postural analysis of the average plantar pressure of the evaluated individuals. No statistical difference was observed in the mean plantar pressure values between the groups ($p = 0.35$) during the period in which they remained in the orthostatic position. Table 3 shows the activity of the ANS based on heart rate variability, and no changes were observed between the control and paraplegic groups in the sympathetic and parasympathetic values throughout the study period ($p > 0.05$).

4. Discussion

This study aimed to evaluate the influence of the use of orthostatic equipment for 90 min on cardiovascular parameters, ANS, and plantar pressure in patients with SCI compared to controls. Our results showed the stability of cardiovascular parameters throughout using the exoskeleton for postural elevation. Additionally, the ANS responses were similar in both groups, and the plantar pressure mean always remained equal between the groups. In contrast, the time adaptation of this data over time demonstrated a nonspecific intragroup difference.

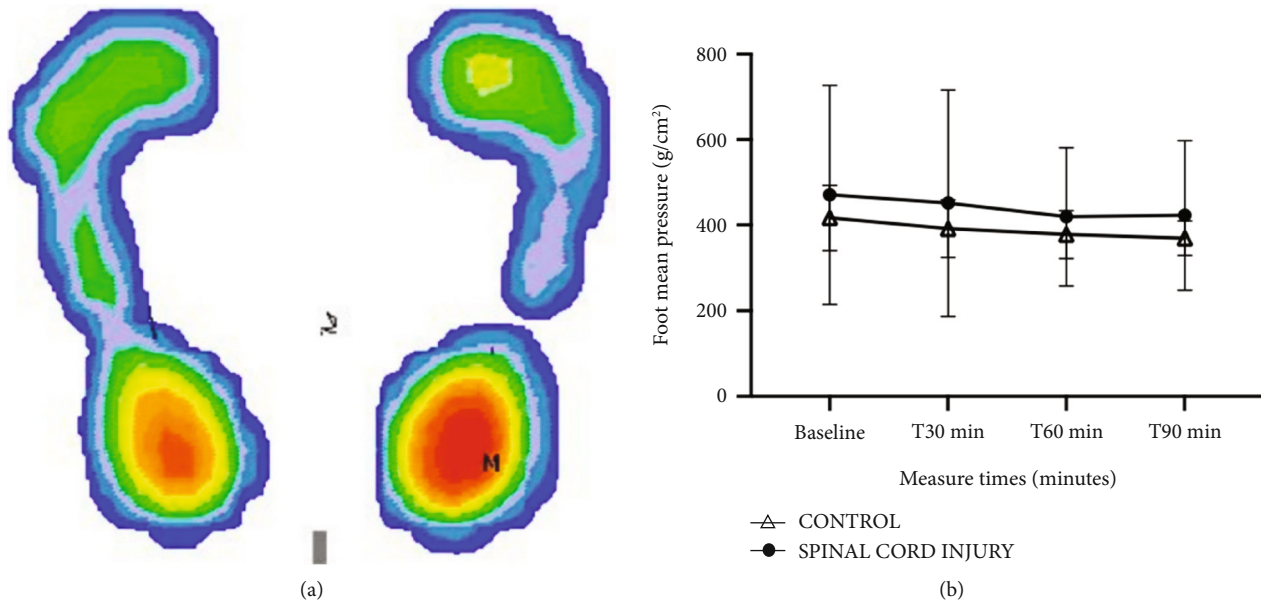

Figure 2: Postural analysis of the average plantar pressure of the evaluated individuals during the intervention period with the exoskeleton. (a) Image of the distribution of the average plantar pressure in the 50 s evaluation interval. (b) Average plantar pressure values every 30 minutes of wearing the exoskeleton in control and spinal cord groups.

Table 3: Functional analysis of the autonomic nervous system.

	Control (N = 15)		Spinal cord injury (N = 15)			
	Mean	(SD)	Mean	(SD)	p value	Mean difference (95% CI)
Sympathetic						
T (0)	0.479	(0.924)	1.072	(1.232)	0.4735	0.593 (−0.471 to 1.66)
T (30)	1.092	(0.745)	1.000	(0.954)	0.9972	−0.092 (−0.927 to 0.743)
T (60)	1.175	(0.761)	1.256	(1.128)	0.9989	0.081 (−0.862 to 1.025)
T (90)	1.053	(0.771)	1.053	(1.241)	>0.9999	0.001 (−1.017 to 1.018)
Parasympathetic						
T (0)	0.702	(1.822)	0.309	(1.834)	0.9624	−0.394 (−2.170 to 1.382)
T (30)	−0.030	(1.575)	0.576	(1.983)	0.8347	0.606 (−1.140 to 2.352)
T (60)	−0.901	(2.487)	0.930	(2.274)	0.1677	1.831 (−0.4863 to 4.148)
T (90)	−0.013	(1.315)	0.418	(1.731)	0.9079	0.431 (−1.070 to 1.932)

SD = standard deviation; CI = confidence interval.

The cardiovascular parameters measured by heart rate, BP, and oxygen saturation in the blood demonstrated that none of the participants presented values that characterized the presence of dysfunction, such as BP [20]. This is an interesting fact, as it differs from a previous study [8] that demonstrated increased BP in paraplegic patients with incomplete SCI during wheelchair elevation for only 15 min [21, 22]. Orthostatic positions in patients with SCI are challenging because BP regulation is required due to orthostatic stress, which generates a displacement of fluids to the lower limbs and abdomen, thus reducing venous return to the heart [23, 24]. This expected response is called autonomically mediated baroreflex, which increases heart rate, contractility, and sympathetic vasoconstriction [21, 22].

The equipment developed and tested in this study had a circulatory support system. The base of the device, where the patient's feet were supported, was designed to move approximately 15° in ankle dorsiflexion, allowing joint mobility and consequently improving venous return and edema. The same system has already been tested in amputees who practiced physical activity for 90 min and showed favorable BP results [25]. Another important point to note is that the use of hip, trunk, and leg fixation straps may have led to greater comfort and a sense of security for the patient, which may have reduced the perception of factors such as anxiety and fear of falling off the floor of the equipment, contributing to greater stability of cardiovascular parameters.

Changes in the ANS can lead to changes in heart rate variability, as heart–brain interactions are essential for vital functions [26]. In this context, SCI can lead to autonomic disorders that increase the risk of developing cardiovascular changes and imbalance between the sympathetic and parasympathetic nervous systems [27]. The literature indicates that autonomic function can improve after exercise, but recommendations on workload monitoring and activity prescription for this population are still scarce [27]. Recent findings by our research group indicate that amputees who practice physical activity can also remain in the orthostatic posture using the same equipment proposed in this study, for 90 min and without changes in autonomic functions [25]. Thus, our data add to the literature the feasibility of using the device and the permanence of the patient with SCI in orthostatism for 90 min in the parameters in question.

The postural control system works such that the upright posture is maintained with the lowest possible energy expenditure, providing control, stability, and balance [28]. Thus, the measurement of plantar pressure was necessary to evaluate the distribution of load in the different plantar regions, as patients with SCI have limited joint mobility and reduced venous return, which can lead to the presence of edema and consequently an alteration in the distribution of pressure throughout the foot [29] during the period of use of the equipment. Patients with SCI have a higher risk of developing pressure ulcers caused by motor and sensory changes, skin changes, and prolonged periods of immobility [29], which were not observed in the feet of the evaluated patients. Thus, the data from this study demonstrate that standing for 90 min did not generate changes in the plantar pressure of patients with SCI compared with the control over the time of use.

4.1. Study Limitations and Strengths. The results in both groups concerning the stability of the cardiovascular parameters during device use for 90 min represent the main strength of this study. Using orthostatic equipment or wheelchair elevation devices could represent a new, safe, and effective technology to help individuals with paraplegia assume a standing position, thus allowing them more mobility [28]. On the other hand, our study has shown that the cardiovascular and postural effects of using orthostatic equipment during long-term continuous conditions, such as work journeys, have not yet been studied. Another limitation was the impossibility of using continuous BP and heart rate monitoring equipment, which prevented us from having more effective control over the variation of these parameters at all times.

4.2. Future Directions. This study demonstrates physiological stability for using the exoskeleton by healthy individuals and individuals with SCI for 90 min. Considering that exoskeletons allow overcoming environmental barriers, acting as part of a rehabilitation process [26], this study opens the possibility of verifying the neurophysiological aspects of the continuous long-term use of the device. In addition, it can boost new studies with more vulnerable populations, such as quadriplegics, hemiplegics, and patients with neurological syndromes, both at home, at work, and in a therapeutic context.

5. Conclusions

The present study showed the absence of difference between SCI patients and control participants using the orthostatic device in terms of cardiovascular and biomechanical parameters (heart rate, oxygen saturation, BP, and plantar pressure distribution) for 90 min, allowing, in clinical practice, the patient to remain in an orthostatic position for longer than reported so far in the literature.

Data Availability

The data can be found in the Local Committee of Ethics in Research (number CAAE 07192819.6.0000.5038) and access to raw data can be shared with reasons and contact with authors.

Ethical Approval

This study did not require public trials registry. This study was approved by the Local Committee of Ethics in Research (number CAAE 07192819.6.0000.5038).

Conflicts of Interest

The authors declare that there is no conflict of interest about the judgment and validity of the results presented.

Funding

The authors declare financial support for the development of this study by Dell Computers, developed at Ceará State University under the project entitled "Technologies for job accessibilization in Brazilian Electronic Industry" within the scope of the STEVE project, through research grants to the authors, allowing data collection and support for the development of the equipment used in the collection.

Supplementary Materials

Table 02 –Comparison of cardiovascular parameters over 90 minutes of maintaining the orthostatic position. *(Supplementary Materials)*

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Hindawi
Applied Bionics and Biomechanics
Volume 2022, Article ID 8645165, 9 pages
https://doi.org/10.1155/2022/8645165

Research Article

A Deep Learning Model for Stroke Patients' Motor Function Prediction

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Received 13 June 2022; Revised 29 June 2022; Accepted 16 July 2022; Published 5 August 2022

Academic Editor: Xianyi Zhang

Deep learning models are effectively employed to transfer learning to adopt learning from other areas. This research utilizes several neural structures to interpret the electroencephalogram images (EEG) of brain-injured cases to plan operative imagery-computerized interface models for controlling left and right hand movements. This research proposed a model parameter tuning with less training time using transfer learning techniques. The precision of the proposed model is assessed by the aptitudes of motor imagery detection. The experiments depict that the best performance is attained with the incorporation of the proposed EEG-DenseNet and the transfer model. The prediction accuracy of the model reached 96.5% with reduced time computational cost. These high performance proves that the EEG-DenseNet model has high prospective for motor imagery brain-injured therapy systems. It also productively exhibited the effectiveness of transfer learning techniques for enhancing the accuracy of electroencephalogram brain-injured therapy models.

1. Introduction

The brain signal acquisition model (BSA) is a message model that can learn brain actions connected to patients' objectives and transform them into control motion. BSA models are widely utilized in therapy of brain-injured cases. EEG signals deliver a noninvasive resolution for the BSA model and are utilized in most brain signal systems. BSA systems have the following phases: signal reading, image analysis, controller apparatus, and signal forwarding [1–4]. The brain signal system paradigms using EEG are based on steady-state motor imagery control systems [5, 6]. Without muscle contraction, the imagery process comprises variations of muscle stimulated by the brain [7–11]. In the presented article, EEG signals are collected from cases with physical disabilities for brain-injured patients. Occupational therapy using motor imagery BSA models can motivate the injured motor to revive the nerves surrounding the injured brain parts and partly reinstate the cases ability.

Deep learning techniques are used for BSA systems, the EEG feature selection, prediction, and detection models [12–16]. The authors in [15] proposed a SVM model to predict two classes of motor imagery signals. The authors in [16] presented two weighted process prediction models, attaining higher accurate prediction [17]. EEG prediction using deep learning can outperform classical models on large database. Such models can designate properties without feature engineering. This marks the neural model a significant selection for handling motor imagery signals using on BSA. Recent research utilized various deep learning models to extract deep features from EEG signals. The authors in [15] proposed a convolutional neural network with an encoder with higher prediction accuracy than classical prediction models on the BSA EEG-2b dataset. Authors in [16] presented a belief deep learning prediction model using the Boltzmann model. Authors in [18] presented the envelope map of EEG signals by employing the Hilbert technique and constructed a motor imagery-based BSA prediction

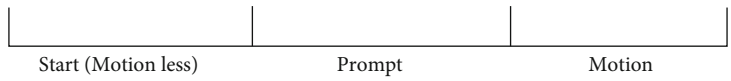

Figure 1: Data gathering process of the simulation.

Table 1: Motricity index scores.

Motor function	Mean	Standard deviation	Minimum	Maximum
Shoulder flex	2.67	0.72	0	4
Elbow flex	2.81	0.68	0	4
Wrist extensor	0.51	0.67	0	2
Finger extensor	0.15	0.35	0	1
Finger flex	0.96	0.87	0	2
Hip flex	2.71	0.63	0	4
Knee extensor	1.71	0.73	0	3
Ankle flex	1.96	0.87	0	3
Toe flex	0.86	0.77	0	2

deep model. They employed the model to the BSA EEG-2 dataset and exhausted the most progressive prediction accuracy stated. Authors in [16] utilized a deep learning model depiction of multiple channel EEG signal to enhance the accuracy. The authors in [17] developed a novel 3D map vectors of EEG signals with a multi-CNN and the linking prediction model. Their system has accomplished high performance. In concept, deep learning attains operative EEG feature selection and better accuracy classification [18–20]. Nevertheless, because of the bad medical state and pervasiveness of brain-injured cases, the EEG capturing is hard with an effect on the structure of great-size dataset. The application of these models for motor imagery studies in brain-injured cases is restricted. Our model uses transfer learning process, which can efficiently tackle the mentioned challenges [21–25]. Transfer learning process is completed by transferring continual or switching discriminated data between cases. Features selected by transferal learning have resemblances and inheritance [26–28]. These features can be defined in a small-sized dataset and can confirm the efficiency of EEG deep CNN models [29–33].

In this research, the paper's contribution is as follows:

(i) Proposing a deep learning models with several extensions and parameter fine tuning using deep process

(ii) Enhancing the accuracy of the BSA model for the recuperation of brain-injured patients, this research employs these deep model to process the EEG signals of brain-injured cases

(iii) The presented model is to incorporate fine tuning with neural and transfer learning leading to the proposed EEG-DenseNet model to detect motor imagery settings

(iv) This research approves the model within the cases to assess the accuracy of all other models. By evaluation the experiments of compared models, it can be proven that EEG-DenseNet outperforms other transfer learning models in all other platforms. The expected performance of our model scopes 96.5% accuracy for both left hands and right hands

The remainder of this paper is organized as follows: Section 2 presents the dataset description. Section 3 introduces the proposed models and presents the experimental results and compare it versus other deep learning systems for motor imagery BSA system. Section 4 depicts the proposed models extension, while Section 5 produces the conclusions and discussion.

2. Dataset Description

The EEG signal is captured from 100 cases (60 brain-injured patients and 40 healthy cases). The simulation utilizes 64-channel EEG reading device to gather data from brain-injured cases (EEG signals with motor imagery). Each experiment proceeds for 0.5 minutes; the details of one experiment is depicted in Figure 1. The recording begins with half the time of the motionless signal. Succeeding a prompt, EEG motor imagery signals are recorded for 6 seconds. There are prompts at the start and finish of motor imagery task. The sampling of signal reading has frequency of 960 Hz. In the gathering procedure, cases track the prompts to make imagery motions, such as hand movement. The time exhibited by the prompt is half the 0.5 minutes time line. The time for a single task is 6 seconds, and it includes a single sort of activity. The pause between successive actions is 5 seconds. The prompts for the hands movement acquirements are random. The simulation includes 50 hand motor acquisition.

These data items are recorded and labeled in a public dataset that we utilized for our experiments [15]. The statistics of the motor function data is depicted in Table 1.

2.1. Preprocessing Task. Preprocessing task comprises cleansing and downsizing. In this research, a 12–32 Hz low pass filter is utilized to remove noises [20], and then, the frequency rate is decreased from 960 to 60 Hz. EEG signals are usually tainted with the 40 to 60 Hz frequency with nosiness from wires and other apparatus which are seized by electrodes of the acquisition device. The signal is saved in map presentation (N, M, and S). N is defined as the count of recordings trials and is set to a constant equal to 3 which is usually enough. M defines the channels number; S defines the count of sampling items per channel. This research utilizes the brain-injured patients' EEG that has motor imagery containing hand movement. The data recorded for each case

Table 2: Parameter of EEG-DenseNet: T = temporal filter, DP = depth, P = point filter. K is the count of motor imagery units.

Structure	Layer	Filters	Size	Output	Activation
	Input: input layer			$M \times S$	
	Reshape: first convolutional layer (CL)			$1 \times M \times S$	
	Second CL	T	(1, 64)	$T \times M \times S$	Linear activation function
	Normalization			T× M × S	
1	Depth CL	DP × T	(C, 1)	(DP × T) × 1 × S	Linear activation function
	Batch sizing			(DP × T) × 1 × S	
	Nonlinear activation layer			(DP × T) × 1 × S	ReLu
	Max pooling		(1, 4)	(DP × T) ×1 × S/4	
	Dropout layer (one out of four)		Probability (pr) = 0.25 or pr = 0.5	(DP × T) × 1 × S/4	
2	Separable CL	P	(1, 16)	P × 1 × S/4	Linear activation function
	Batch sizing			P × 1 × S/4	
	Nonlinear activation layer			P × 1 × S/4	ReLu
	Max pooling		(1, 6)	P × 1 × (S/16)	
	Failure layer		Probability = 0.35 or probability =0.6	P × 1 × (S/32)	
	Flattening out			P × S/32	
Classifier	Dense classified fully connected	K × (P × T/32)	Norm = 0.25	K	Softmax

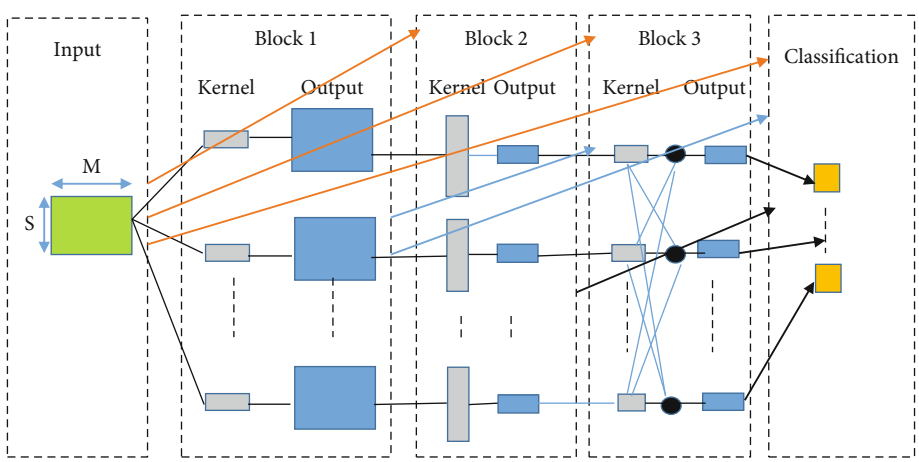

Figure 2: EEG-DenseNet structure.

is divided into three data subsets namely: training, validation, and testing. There is a 100 trial recording for each case including motor imagery task. For each case, 90 data items are utilized for training, 15 for validation and 15 for testing. Randomly, K cross-validation is used where $K = 12$, to compute the expected accuracy of each case. We have 40 healthy people and 60 brain-injured patients.

2.2. Deep Learning Phase: The Proposed EEG-DenseNet Model. EEG-DenseNet is a dense CNN model for handling EEG signals. It is trained with small-sized dataset, and it can yield a neuro instruction. Table 2 displays the graphical construct and the definite factors of the EEG-DenseNet deep system. The input has dimension of (M and S): M defines the channels number, and S defines the count of sampling items per channel. This research utilizes the Adam optimizer [18, 20, 21] and optimizes the entropy loss ReLu function. The proposed EEG-DenseNet is depicted in Figure 2.

2.3. Incorporation of Fine Tuning in the EEG-DenseNet. The efficiency of transfer learning is influenced by many parameters. One of these parameters is correspondence among the

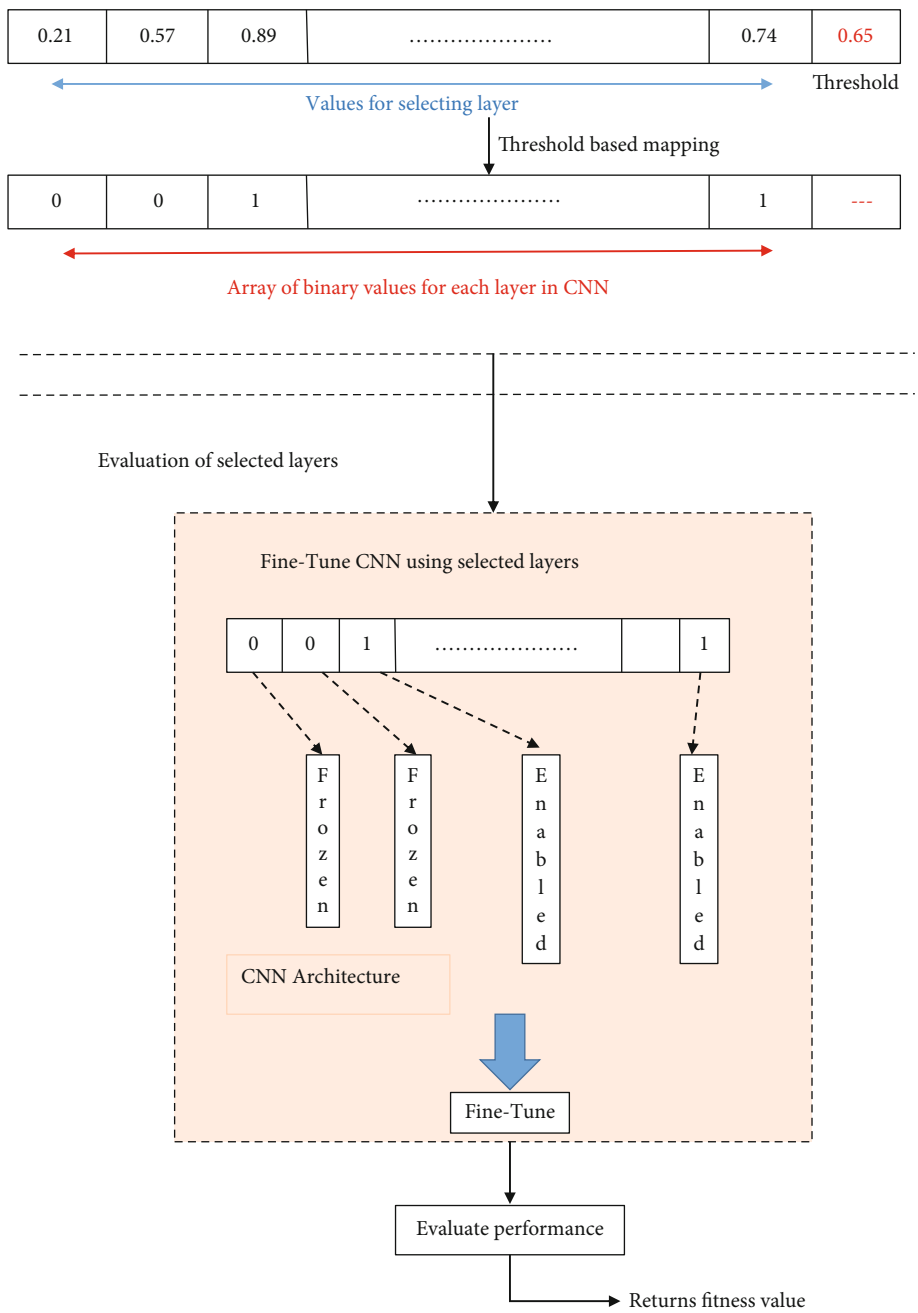

Figure 3: Fine tuning of the convolutional layers.

training source input and the destination signals. The greater the correspondence, the greater the fine tunings outcome. The factors attained by the initial input and CL of the EEG-DenseNet are the elementary factors (for instance, selecting a definite visual filter from the initial layers) [31–36]. The last layers select definite features (for instance, the system can recap the feature representation map distinctly and get the finest feature maps). In the simulation, the database size is rather small. To evade overfitting, the tuning of the deep learning model is done into the depicted stages:

(i) Adjust the factors of the output layer. Our model uses transfer learning for the initial layers, and adjust the classifier parameters

(ii) Modify the model CL parameters to fittingly diminish the learning level and epochs count. The learning level is comparatively low because the operative system weights are utilized for model tuning. If the learning level is elevated, the system can be modified rapidly and dismisses the initial weights. After tuning, this research selects to update

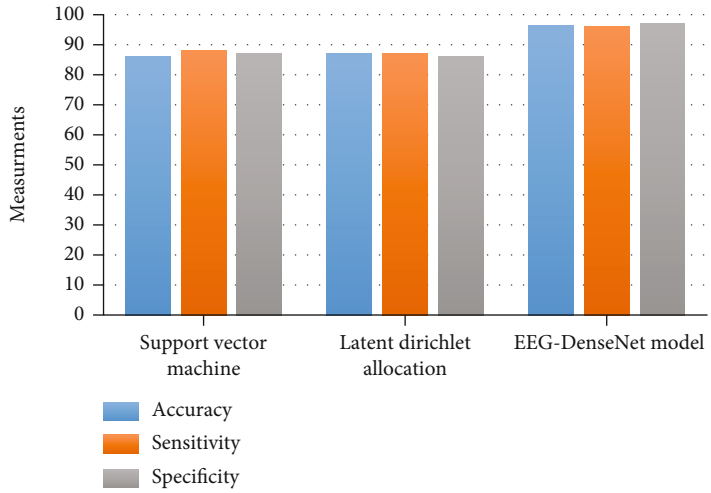

Figure 4: The expected prediction performance of the compared model versus our proposed model models.

Table 3: The parameters of our model.

Model parameters	Value
Learning level	0.0002
Dropout rate	0.6
Number of epochs	200
T	8
P	12
DP	3

Table 4: Prediction results attained by various tuned models.

Subject	Accuracy (%)		
	Proposed model	Support vector machine	Latent Dirichlet allocation
C1	97	87	84
C2	96	87	84
C3	93	77	87
C4	97	84	87
C5	94	74	84
C6	94	77	87
C9	95	84	87
C6	96	77	77
C9	98	84	74
C10	97	87	87
C11	94	87	74
Mean	98.7	84.47	79.49
Standard deviation	±4.7	±3.8	±3.4

all parameters [37, 38]. The EEG-DenseNet model was formerly executed on large datasets, which undetectably extended the previously trained data, and its accuracy is valuable to the new dataset. Hence, fine model tuning will enhance the model to attain higher results utilizing only limited number of epochs

(iii) Begin the training stage and compute the parameters of the transfer learning model

The proposed model utilizes both the EEG feature selection captured in the transfer learning model and fine model tuning. This creates a robust adaptive model with parameter tuning for better motor imagery recognition.

Fine tuning randomly set the weights of the pretrained network. Different datasets are utilized in the neural convolution for relearning. Also, weights are utilized on the preceding convolutional layers, and the preliminary weights on the preceding layers are set. The experiments produce better grouping of the unused layers and the fine-tuned layers, as depicted in Figure 3.

3. Results and the Prediction Performance

Our research uses the training, validation, and testing datasets of each case into the deep learning models under comparison along with our model. Figure 4 displays the depiction of the expected precision of a single deep learning method. As perceived, the EEG-DenseNet method achieves the highest precision. The expected prediction precision of the EEG-DenseNet method from all cases is reaching 96.5%. The model learning parameters are depicted in Table 3. The expected total accuracy of healthy cases and brain-injured cases is depicted in Figure 2. We evaluated the statistical t-test of the prediction performance linking to the 100 cases using the support vector machine, latent Dirichlet allocation, and our EEG-DenseNet model, with p value of 5.19×2^{-10}. It is depicted that pr is about 0.055, and the prediction precision has shown momentous variances. It implicates that enhancement of our model is higher. For the input signals, prediction accuracy of the support vector machine, latent Dirichlet allocation classifier, and our model are investigated, and the experiments are

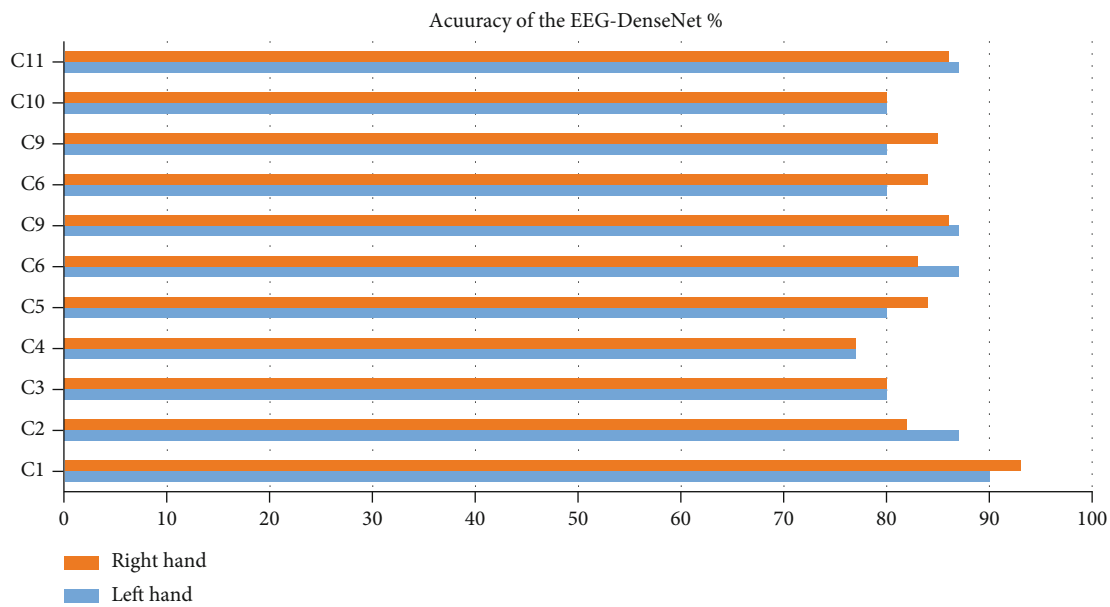

Figure 5: The accuracy of the EEG-DenseNet for 11 cases C1 to C11 (6 healthy: C1 to C6 and 5 brain-injured patients C7 to C11).

Table 5: Prediction accuracy results realized by the different extension models for both hands movements.

Case	EEG-DenseNet_E1 (%)		EEG-DenseNet_E2 (%)		EEG-DenseNet_E3 (%)	
	Left hand	Right hand	Left hand	Right hand	Left hand	Right hand
C1	87	86.5	97	96	90	93
C2	80	80	97	98	87	82
C3	77	89	87	88	80	80
C4	77	86	87	85	77	77
C5	80	80	87	88	80	84
C6	87	87	90	94	87	83
C9	87	86	90	90	87	86
C6	80	80	87	89	80	84
C9	77	85	97	88	80	85
C10	77	84.9	87	86	80	80
C11	77	86	90	97	87	86
Mean	79.09	89.09	98.7	98.8	82.29	85.7
Standard deviation	±2.3	±4.3	±3.4	±4.1	±1.9	±3.3

depicted in Table 4. It can be proved from the precision of our model that it outperforms other classifiers. In Figure 5: the accuracy of the EEG-DenseNet for 11 cases C1 to C11 (6 healthy: C1 to C6 and 5 brain-injured patients C7 to C11) is depicted.

We used the following definitions for the accuracy, sensitivity, and specificity:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}}, \tag{1}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \tag{2}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FN}}, \tag{3}$$

where TP is the true positives, TN is the true negatives, FP is the number of false positive cases, and FN is the number false negative cases.

4. The Proposed Model Extension

4.1. Accuracy. Three extension models have been developed on the proposed EEG-DenseNet method. The starting model is to statistically set the parameter of the deep learning model; then, a different subset is fed in for model (the extension method is named EEG-DenseNet_E1).

The second extension model is to halt the variation of the weights in the block 1 of the proposed CNN in the transfer learning model and start retraining the other layers such that different weights can be attained (the processed extension model is called EEG-DenseNet_E2).

The third extension model is analogous to the second extension model, with the weights of both blocks in the proposed CNN unchanged (the processed extension model is called EEG-DenseNet_E3).

The three extension systems are compared. The expected prediction accuracies of 11 cases are depicted in Table 5. It depicts the accuracy of the various extension models. The second model has the best prediction result.

It can be depicted from Table 6 that the prediction accuracy of the EEG-DenseNet_E2 model outperforms the other two extension models. The performance results prove that model of partly unchanging parameter values is higher than the other model of the total model weight starting point. It can be depicted from Table 6 that the prediction performance from EEG-DenseNet_E2 model is higher than the

Table 6: Floating-point operations per second and training CPU time of training of all methods.

Method	Average accuracy (%)	Average sensitivity (%) (percentage of patients with a dysfunction case who predicted as positive)	Average specificity (%) (percentage of patients without a dysfunction case who predicted as negative)
EEG-DenseNet	97.6%	98.1%	97.9%
DenseNet	92.4%	93.2%	92.8%
Xception	91.4%	91.6%	92.1%
ResNet	89.7%	89.8%	88.7%
VGG16	87.4%	88.2%	88.6%

Table 7: Floating-point operations per second and training CPU time of training of all methods.

Method	Floating-point operations per second (millions per second)	Average minutes	Standard deviation
EEG-DenseNet	0.052	142	±8.9
DenseNet	2.479	470	±8.7
Xception	6.243	409	±10.8
ResNet	3.965	616	±12.9
VGG16	13.15	855	±14.6

Table 8: Floating-point operations per second and training CPU time of classification all methods.

Method	Floating-point operations per second (millions per second)	Seconds
EEG-DenseNet	0.0052	12
DenseNet	0.179	40
Xception	0.243	49
ResNet	0.765	66
VGG16	0.815	85

Table 9: Statistics for using EEG-DenseNet model with and without fine tuning.

	EEG-DenseNet model classifier without fine tuning	EEG-DenseNet model classifier with fine tuning
Correctly predicted	0.871	0.971
Incorrectly predicted	0.139	0.039
Qualitative reliability	0.197	0.321
Average square error	0.872	0.321

Table 10: Confusion matrix for the EEG-DenseNet model with fine tuning for 100 cases for left hand.

		Classified cases	
		Positive	Negative
Actual cases	Positive	50	6
	Negative	4	40

results of the EEG-DenseNet_E3 model. The reason for that is that the selected features in the second one are the definite features linked to the motor imagery. By keeping the parameter values of the second block unchanged, the capability of model classification is decreased, so the accuracy is reduced.

As a final note, the experimental results realized from the EEG-DenseNet_E2 model are as shown: in the EEG-DenseNet method, it is proven that deep factors are selected in the first one, while more specified features are extracted in the second block of the CNN structure.

Performance comparison between our model and other models in terms of accuracy is depicted in Table 6.

4.2. Computational Complexity. In deep learning model, time complexity measurement is one of the norms for computing the model performance. The novelties of several models are established using the time computational complexity. To minimize time complexity, we substitute the multiplication operations into parallel addition operations. In this article, the research computed the floating-point operations per second (FLOPs) of all models to compute the time and space computational load of the proposed model [27].

The count of the FLOP operations controls the training time and the classification time of the proposed model. If the CPU time are getting time consuming, it can affect the model training and classification CPU time to need a high time complexity, and it is impossible to achieve the real-time requirements.

Memory requirements (MEM) are also important to compute the separability of the hardware modules of the module functionality. MEM computes the count of factors for optimizing the method. In memory restriction, the higher the number of the method parameters, the greater the quantity of input needed for model training. The size of the input in actual situations is typically not too high that deems the system modeling overfits.

In this article, floating-point operations per second and MEM of all the methods are utilized to compute the time and space computational load, as depicted in Table 7. It is shown from the mentioned table that the requirements for the EEG-DenseNet training are less than the other compared models, thus decreasing the count of operations and the parameters to fit real-time requirements. The training computation time of the EEG-DenseNet model is lower than other compared models. Table 8 depicts the time and space requirements for the compared model classification.

In Table 9, we display the statistics for using EEG-DenseNet model with and without fine tuning depicting the correctly and incorrectly predicted cases. Also it declares

Table 11: Confusion matrix for the EEG-DenseNet model with fine tuning for 100 cases for right hand.

		Classified cases	
		Positive	Negative
Actual cases	Positive	53	4
	Negative	3	43

the qualitative reliability Kappa metric as well as average square error. From Table 8, it is clear that incorporating fine tuning in the deep learning model will accentuate the model performance.

In Tables 10 and 11, we display the confusion matrixes for the EEG-DenseNet model with fine tuning for 100 cases for left hand and right hand.

5. Conclusions

In this article, the research was to determine if the proposed EEG-DenseNet model that incorporated fine parameter tuning with deep learning can be efficiently utilized for small-sized input. The presented model is primarily used for the input signals of normal cases and brain-injured cases. The simulation can prove that the total prediction results of healthy cases are higher than brain-injured cases. It is more difficult to capture EEG signals from brain-injured cases as well as very costly. Brain-injured patients have hard time staying motionless without eye blinking or involuntary movements that frequently infect the captured EEG signals. Moreover, brain damage can extremely alter the lively properties of the EEG data, thus aggregating the uncertainty of the EEG distribution. It is an important issue to attain a large size and better quality EEG signals from brain-injured cases. It should be noted that the accuracy of patients' EEG actions may not accomplish the required effect, which are prospective parameters impacting the final performance results.

This article investigated the input data of the whole cases both healthy and brain-injured patients to clarify the efficacy of the data communication of models with transfer learning. These neural structure models are motivated by image processing and feature extraction. The universal features of all cases can be learned through the initial CL model layers. Deeper more specific features are extracted from experimental training. This research can use small-sized databases by ceasing the prior layers of transfer learning and diminishes the count of model parameters that has to be maximized. This research indicates that the presented model can transfer learning for the same pattern. The experimental results depict that transfer learning should be incorporated in the paradigm of EEG processing. The EEG-DenseNet outperforms other state-of-the-art neural deep learning models in motor imagery detection. The experiments prove that we can utilize small-sized dataset for training. The learning process are efficiently done on the EEG signals of brain-injured cases via transfer learning modeling.

Data Availability

Data are available upon request from the authors.

Conflicts of Interest

Authors declare that there is no conflicts of interest.

Acknowledgments

We would like to thank the Princess Nourah bint Abdulrahman University Researchers, Riyadh, Saudi Arabia, for supporting our project with number PNURSP2022R113.

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Hindawi
Applied Bionics and Biomechanics
Volume 2022, Article ID 6106943, 8 pages
https://doi.org/10.1155/2022/6106943

Research Article

Isokinetic Assessment of Shoulder Joint Strength Ratios in Male Recreational Weightlifters: A Cross-Sectional Study

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Received 22 March 2022; Revised 7 May 2022; Accepted 19 May 2022; Published 13 June 2022

Academic Editor: Qichang Mei

Background. Isokinetic strength imbalance is a risk factor for movement dysfunctions and injuries related to shoulder complex. The effects of recreational weightlifting on developing the imbalances between the shoulder muscles are not yet known. *Objectives.* To investigate the isokinetic concentric shoulder muscle strength values (peak torque normalized to body weight) in recreational weightlifters (RWL) and to compare the shoulder muscles agonist/antagonist ratios with nonweightlifters. *Methods.* Thirty male RWL with mean age, weight, height, and body mass index (BMI) of 21.56 years, 84.25 kg, 175.34 cm, and 26.51 kg/m^2, respectively, matched with nonweightlifters served as a control group. The normalized concentric peak torque values of shoulder flexors, extensors, abductors, adductors, and internal and external rotators were measured at angular velocity 120°/sec by using Biodex isokinetic system. Moreover, the agonist/antagonist strength ratio for all muscle groups were calculated. *Results.* The normalized peak torques of RWL group were significantly greater than the control group ($p < 0.05$). The abductor/adductor and external rotator/internal rotator ratios of the RWL were significantly lower than the control group ($p = 0.008$ and 0.009, respectively). Conversely, there was no significant difference between both groups in relation to the flexor/extensor ratio ($p = 0.259$). *Conclusion.* These results suggested that the recreational weightlifting exercises place trainees at risk of muscle imbalances. Therefore, the restoration of a normal concentric abductor/adductor and external rotator/internal rotator strength ratios may decrease the risk of possible shoulder injury.

1. Introduction

Weightlifting is widely used for various health benefits such as sports [1], injury rehabilitation, maintenance of cardiorespiratory and muscular fitness [2], and the development of muscle hypertrophy and shaping [3]. It is estimated that almost 45 million Americans are regularly engaged in weight training programs [4]. However, weightlifting is associated with numerous injuries. The lower back followed by the shoulder and knee joints are the most frequently affected areas [5]. According to Kerr et al. [6], shoulder injuries account for 36% of all injuries and disorders in the weightlifting trainees.

Two main types of exercises are incorporated in weightlifting training programs: complementary exercises that have movement patterns similar to the competitive lifts (e.g., hang/power snatch) and supplementary exercises (e.g., overhead presses) that target synergistic muscle groups [7]. Many muscle contractions are performed by the same major muscle groups during each training session. The frequency of lifting might exceed evidence-based recommendations for improving muscular strength and power [2]. Most adopted weightlifting training programs are designed based on multiple sets of submaximal to maximal muscle loading to match the demand during competitive practices. It was

estimated that weightlifters performed between 1400 and 4000 maximal attempts, and 450 and 460 failed supramaximal attempts each year of training [8].

Muscular balance is crucial for normal shoulder function. Both static and dynamic situations of the shoulder joint depend, to a great extent, on balanced muscular strength and power. Dynamic situation is a function of deltoid muscle as prime mover balanced by the force of gravity and infraspinatus, subscapularis, and teres minor muscles [9]. In the same context, the balance between trapezius and serratus anterior muscles serves as the primary mechanism in upward rotation of scapulothoracic joint, which is necessary for arm elevation [10]. Disturbance of the previously mentioned force couples is a common risk factor in many shoulder injuries [11, 12]. In recreational weight training (RWT), muscle imbalance results from training large muscles called mirror muscles (pectoralis, deltoid, and upper trapezius muscles) at the expense of the shoulder complex stabilizers [13]. This imbalance exposes the recreational weightlifting trainees to a high risk of injuries [14].

Muscular imbalance and improper technique can both impair athletes' performance and put them in danger. A prolonged clean and jerk motion, which is thought to be the fundamental movement for weightlifting, appears to aggravate muscular imbalances, leading to an increased risk of injury [15]. A recent study reported imbalance of the isokinetic profiles of rotator cuff muscle strength and power between both upper limbs in adolescent weightlifters [16]. Muscle strains, ligament sprains, pectoralis major tendon ruptures, distal biceps tendon ruptures, chronic shoulder pain, and capsulolabral injuries are all common upper extremity injuries in resistance training athletes. While each injury is unique in its anatomic location and mechanism, they are all preventable with proper exercise technique, safety, and muscle balance maintenance [4].

A literature review showed that no previous studies have investigated muscle imbalances in RWL. Moreover, this may help physical therapists, strength coaches, and athletic trainers in designing an effective and safe shoulder resistance training. So, the aim of the current study was to assess the isokinetic concentric shoulder muscle-normalized torque values and to compare the agonist/antagonist ratios of RWL with nonweightlifters. It was hypothesized that there will be a difference between groups in terms of normalized isokinetic torques in the favor of RWL group with no difference in terms of the agonist/antagonist ratios.

2. Methods

2.1. Participants. This cross-sectional study was conducted on thirty male RWL with age range from 18 to 30 years (study group) who were recruited from local fitness centers. They were matched with a similar number of nonweightlifter (healthy) subjects with similar demographic data as the control group. The weightlifters should be involved in upper extremity resistance weight training at least three times per week for the previous six months [17]. Participants were excluded if they used anabolic steroids and participated in professional bodybuilding, competitive power lifting, or other overhead sports. The nonweightlifters were excluded if they participated in a formal type of upper extremity resistance training exercise and if they had a history of upper extremity or neck symptoms. Shoulder pain or injury at the time of the study was an exclusion criterion for both groups. Demographic data of the study and control groups are shown in Table 1.

Before the beginning of the study, the local university's ethical committee reviewed and approved all procedures (ID:P.T.REC/012/00728). Participants were oriented about the purpose and procedures of the study and signed an informed consent. Using G∗Power 3.1 software, the sample size was calculated to be 30 participants in each group. The alpha value, power, and effect size were set at 0.05, 0.90, and 0.85, respectively.

2.2. Procedures. For data collection, the nondominant arm was used to avoid the effect of dominance on isokinetic strength [18]. Based on motor skills, dominant arm was defined as the one preferred for daily activities such as eating, writing, cutting, and catching [19]. The shoulder exercises and the number of exercise repetitions each participant performs in his routine workout were provided. Different types of upper extremity weight training exercises (lever inclined chest press, butterfly, bench press with barbell, dumbbell one arm row, cable standing fly, bench press with dumbbell, decline and incline bench press with barbell or with dumbbell, dumbbell fly, lever shoulder press, assisted pull up, reverse butterfly, neck press with dumbbell, lateral deltoid raise, reverse fly with dumbbell, diagonal lateral cable raise, upright cable row, and cable external rotation) were presented in special sheet from which participant chose exercises he usually practiced in his weight training. A summary of the study procedures is presented as a flowchart (Figure 1).

An isokinetic muscle testing protocol was set for the three shoulder movement patterns in the concentric/concentric mode of muscle contraction after system calibration. Angular velocity of 120°/sec was chosen for this study protocol (the recommended testing velocity during the assessment of muscle imbalances) [20]. Moreover, peak torques were normalized to body weight to avoid the effect of weight differences of the participants [21]. Each set consisted of five repetitions as shoulder muscle peak torques were found to be developed during the second or third test repetition in 96% of all cases [22]. Warm up preceded the actual assessment consisted of five minutes of pendulum exercises followed by two sets of dynamic stretching of shoulder flexors, extensors, abductors, adductors, and internal and external rotators, each taking 20 seconds per muscle group [23].

Each participant was positioned in a comfortable sitting position on the Biodex chair with the trunk positioned upright and the hips and knees at approximately 85° flexion. The trunk was supported up to the scapular level by a firm back and stabilized using a combination of pelvic strap and a pair of anterior straps which were stretched diagonally from just above the shoulder level to the opposite pelvic side, crossing each other at the lower part of the sternum. A single strap was applied horizontally across the thigh of the tested side.

Table 1: Demographic data of the control and RWL group.

	Control group, $n = 30$	RWL group, $n = 30$	p value
Age (years)	20.65 ± 1.87	21.56 ± 3.31	0.331
Weight (kg)	73.39 ± 15.38	84.25 ± 12.88	0.034*
Height (cm)	172.94 ± 8.26	175.34 ± 8.03	0.196
Body mass index (kg/m^2)	24.90 ± 2.06	26.51 ± 2.13	0.635

Data are presented as mean ± standard deviation. p value < 0.05 means significant difference. RWL: recreational weightlifters.

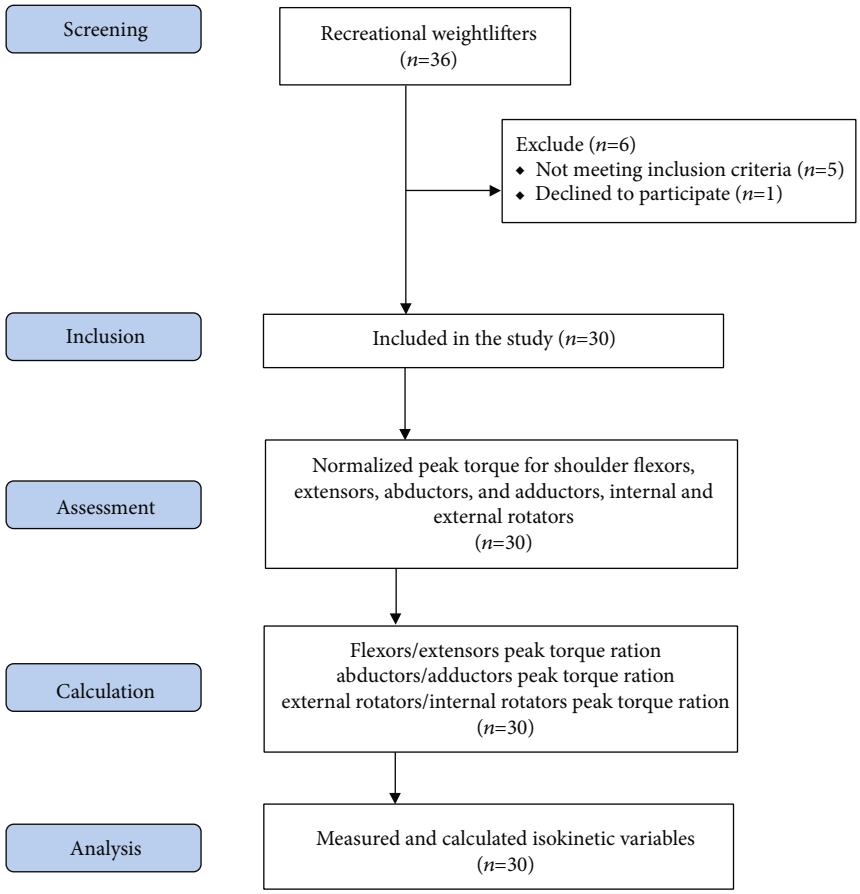


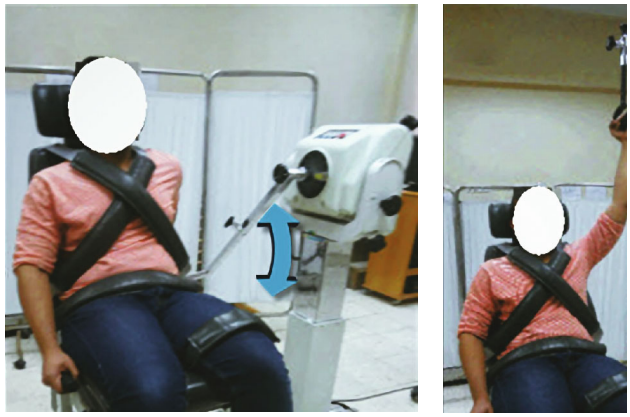
Figure 1: Flowchart of the study procedures.

Abduction/adduction movement: the participant sat in front of the actuator with trunk upright, hips and knees flexed, elbow extended, and forearm supinated. The mechanical axis of lever arm was aligned with an anatomical point just below the acromion, the dynamometer was tilted 10°, seat oriented at 90 degrees, and seatback tilted 70-85°. The range of movement was set free between the hanging position and 120° shoulder abduction (Figure 2).

Internal/external rotation movement: the participant sat with trunk upright, hips and knees flexed, and the arm abducted 90° in the scapular plane and supported. The mechanical axis of lever arm aligned to the long axis of the humerus, dynamometer orientated 20° and tilted 10 to 15°, seat orientated 15°, and seatback tilted 55 to 85° according to participant's anthropometric measurement. Limits of the shoulder ROM were set at 30° internal rotation and 90° external rotation so that the shoulder externally rotated throughout a 120° (from 30° internal rotation to 90° external rotation), as shown in Figure 3.

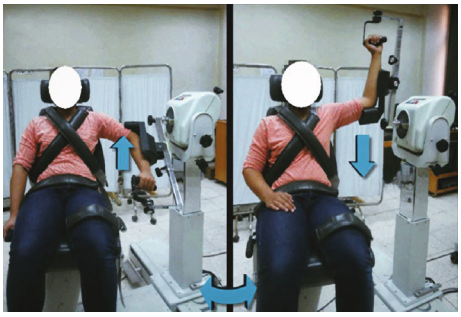
Flexion/extension movement: the participant sat with trunk upright, hips and knees flexed with the axis of lever arm aligned at acromial process in sagittal plane, and seatback tilted 70 to 85°. Limits of the shoulder ROM were set at 60° shoulder extension and 180° shoulder flexion so that the shoulder flexed throughout a 240° (from 60° extension to 180° flexion), as presented in Figure 4.

Afterward, gravity correction was performed for each participant as indicated by the Biodex system 3 manual. Prior to each test, the participant was familiar with the dynamometer by performing three submaximal contractions followed by two maximal contractions at a comfortable speed of 120°/sec,



(a) (b)

Figure 2: Shoulder abductors and adductors isokinetic testing: (a) initial position and (b) final position.



(a) (b)

Figure 3: Shoulder external and internal rotators isokinetic testing: (a) initial position and (b) final position.

(a) (b)

Figure 4: Shoulder flexor and extensor isokinetic testing: (a) initial position and (b) final position.

thus preventing negative transfer of learning resulting from performing only submaximal warm ups and then performing maximal tests [24]. Then, two-minute rest was given to each participant before the actual test. A hand-held remote comfort stop was placed in the participant's free hand before the start of any test session. Then, he was instructed to perform one set of five consecutive maximal concentric contractions at 120°/sec angular velocity. All participants received standardized, consistent, and moderate verbal encouragements. Three-minute rest was given between testing positions as it is enough time for adenosine triphosphate repletion [13].

2.3. Statistical Analysis. All statistical measures were performed through the Statistical Package for Social Sciences (SPSS) version 20 for windows. It was intended to compare isokinetic concentric shoulder muscle strength values and shoulder muscle agonist/antagonist ratios. Checking normal distribution for each dependent variable, in respect to the independent variable, and detecting outliers were conducted through Shapiro-Wilk normality tests and box plots. To avoid the effect of platykurtic data, z-scores for kurtosis were calculated. Data exploration for each set of data revealed that the data of RWL and controls were homogenous and normally distributed. Independent t-test was the statistical procedure used to compare the sample means with respect to the dependent variables. The alpha level was set at 0.05.

3. Results

An independent t-test, comparing the demographic data between both groups, showed homogeneity of groups in these data except for weight as presented in Table 1. Groups were identified based on participation in recreational weightlifting programs.

Regarding isokinetic concentric-normalized peak torques of assessed shoulder muscles, the mean values of all tested muscle groups were significantly greater in RWL than those of the control group ($p < 0.05$), as shown in Table 2.

Regarding the shoulder joint agonist/antagonist ratios, there was a significant decrease in abductor/adductor and external rotator/internal rotator ratios in RWL compared with the control group ($p < 0.05$). Meanwhile, the statistical difference in the flexor/extensor ratio between both groups was insignificant ($p > 0.05$), as shown in Table 3.

Analysis of exercises: the shoulder adductor muscles were the most targeted muscles during training (94%), followed by shoulder extensors (75%), flexors (73%), internal rotators

Table 2: Data analysis of shoulder muscles normalized concentric peak torques (N.m) at 120°/sec.

	Control group, $n = 30$	RWL group, $n = 30$	F value	p value
Flexors	60.68 ± 17.15	87.67 ± 10.61	27.322	0.001*
Extensors	56.30 ± 22.21	85.44 ± 17.32	16.433	0.001*
Abductors	52.12 ± 15.19	67.19 ± 12.98	8.762	0.006*
Adductors	38.19 ± 17.68	69.20 ± 22.97	17.886	0.001*
External rotators	32.29 ± 9.94	43.17 ± 5.70	13.729	0.001*
Internal rotators	33.68 ± 17.95	55.86 ± 19.88	10.657	0.003*

Data are presented as mean ± standard deviation. p value < 0.05 means significant difference. RWL: recreational weightlifters.

Table 3: Data analysis of shoulder muscles agonist/antagonist ratios at 120°/sec.

	Control group, $n = 30$	RWL group, $n = 30$	F value	p value
Flexors/extensors	1.14 ± 0.26	1.05 ± 0.15	1.326	0.259
Abductors/adductors	1.43 ± 0.44	1.04 ± 0.29	7.804	0.008*
External/internal rotators	1.08 ± 0.34	0.81 ± 0.149	7.847	0.009*

Data are presented as mean ± standard deviation. p value < 0.05 means significant difference. RWL: recreational weightlifters.

(71%), and then shoulder abductors (19%), and the external rotator muscles were the least trained muscles (12%). It also revealed that most of muscle groups were exercised for an average of three sets, each set consisted of ten repetitions.

4. Discussion

Firstly, the findings of the current study revealed that the tested normalized peak torques of RWL group were significantly higher than those of the control group. The differences in peak torque between both groups were as follows from the highest to the lowest: adductors, extensors, flexors, internal rotators, abductors, and finally external rotators' peak torques. This descending order in the strength values of different shoulder muscle groups matched the specific types of strength exercises performed by the RWL as indicated from the filled exercise sheet by the participants. The strength difference between both groups is attributed to weight training effects. Resistance training results in both muscular and neural adaptations which in turn increase the muscular strength [25]. These adaptations occur as a result of alterations in hormone levels, neuromuscular junction activity, motor unit recruitment, and changes in the contractile proteins in muscle [26].

The findings of the current study are in agreement with those of Barlow et al. [1] who postulated that the selectivity in the training program with special focus on large muscles as pectoralis major, latissimus dorsi, and deltoid muscles with neglection or undertraining of the stabilizers might be the reason for increasing body weight adjusted strength values of shoulder flexors, abductors, and internal and external rotators among body builders as compared with the controls. Moreover, the present study is aligned with the work of Kolber et al. [13] and Kolber and Corrao [14] in terms of the shoulder abductors and internal rotators' strength values. Both studies reported that the increase in these values is referred to overtraining of deltoids and internal rotators among weight training participants as it was indicated by their routine workouts. In addition, Kolber et al. [27] reported that the upper extremity exercise prescription should concentrate on the internal rotation mobility, alleviates training bias, and favors muscles responsible for stabilization, such as the external rotators and lower trapezius.

Additionally, Kolber and Corrao [14] found a significant increase in the mean external rotator strength value, in the female recreational group compared to the controls. This came in the same context of the present study in spite of the difference in the studied group gender. In the abovementioned study, most of the female participants routinely performed latissimus pull downs towards the body rear. This type of exercise places the shoulder in a position of horizontal abduction combined with external rotation. This shoulder position forces the rotator cuff muscles, along with the external rotators, to work harder to stabilize the head of the humerus [28]. Also, Blache et al. [29] reported that the mechanical work of the rotator cuff muscles, upper trapezius, and anterior deltoid was increased with lifting load and height augmentation.

On contrast to the current study, Kolber et al. [13] found that the difference in shoulder external rotators' strength value between male RWL and controls was not significant. Exercise selection is the key to justifying this disagreement. In the present investigation, participants performed diagonal lateral cable raise and cable external rotation exercises which mainly focus on training of external rotators as prime movers [30]. In addition, they performed reverse butterfly, reverse fly with dumbbells, and shoulder raise lying on the stomach exercises in which external rotators act as stabilizers [30]. With regard to Kolber et al. [13], the only exercise reported by participants that target the external rotators as stabilizers is latissimus pull down to the front [28]. Nonetheless, they did not mention any exercise directly targeting the external rotators.

Another reason for this disagreement may be the difference in testing position. The current study assessed the isokinetic torque of the internal and external rotators, while the shoulder joint is abducted 90°, while Kolber et al. [13] assessed them from a more adducted position. Shoulder adduction changes the length-tension relationship and the line of action of scapulohumeral and axiohumeral musculature putting them in a physiological and biomechanical disadvantage as reported by Davies [31]. Moreover, the training volume should be considered when explaining different strength gains. It was reported that muscle strength gains in response to resistance training are greater with multiple sets per exercise rather than a single set [32]. In the present study, RWL performed external rotator exercises three sets, each set consisted of ten repetitions. On the other hand, exercise parameters were not delineated in Kolber et al.'s [13] study.

Secondly, the current research revealed a significant decrease in abductor/adductor and external/internal rotator ratios in RWL compared to weightlifters. This can be explained mathematically by the fact that the percent of the increase in adductors and internal rotators' strength values is greater than that of abductor and external rotator strength values, respectively. These results correspond to the fact that the percentage of exercises targeting shoulder adductors and internal rotators is greater than exercises targeting abductors and external rotators, respectively.

Moreover, the recreational weight training group had lower flexor/extensor ratio. However, this decrease was not statistically significant, since the difference between strength mean value between both groups, in flexion and extension, was approximately equal. Also, the percentage of exercises targeting the flexors and extensors was nearly the same. Regarding external rotator/internal rotator ratio, the current result is supported by Kolber et al.'s [13] findings who found that the external rotator/internal rotator ratio decreased significantly in recreational weight training group. They declared that this finding may result from the internal rotators being commonly exercised in recreational weight training as compared to the external rotators, which are usually ignored.

Meanwhile, the current result does not concur with Kolber and Corrao [14] who reported a nonsignificant difference in this ratio between both female groups. It was found that, following resistance training, the absolute strength gain in males is greater than females [33]. Moreover, the self-selected resistance load of women often does not exceed 60% of one-repetition maximum (1 RM) which is suboptimal for increasing the muscle strength [34]. Additionally, the differences in training patterns and exercises, the participants selected in both studies, may account for this disagreement.

The current study has many clinical implications as it highlights the risk related to adaptations resulting from participation in recreational weight training [35, 36]. Muscle imbalances identified in this study may place RWL at risk of developing many shoulder disorders which in turn affect balance ability and postural stability [37]. It revealed, for example, that shoulder external rotators are the least exercised muscles, even though there is an inverse relationship between the strength of this muscle group and the incidence of shoulder impingement syndrome among RWL [38]. Furthermore, high loads raised overhead in many shoulder weight exercises may predispose RWL to shoulder pain [39]. Additionally, these exercises are performed in either cardinal frontal or sagittal planes at which the rotator cuff and deltoid muscles are at a mechanical disadvantage with increased risks of impingement or subluxation [40]. More specifically, upright row and lateral deltoid raise exercises are performed by 41% and 24% of the participants, and 19% performed both exercises in the present study. These two exercises are strongly related to the development of shoulder impingement syndrome [38].

The major limitation of this study was the fact that isokinetic dynamometer assesses muscle groups, not the torque of specific muscles. As a result, a separate assessment of the mobilizer and stabilizer muscle groups could not be performed. However, it is still utilized as a gold standard in the assessment of muscular performance [41]. Another limitation is that the study was conducted on male RWL due to cultural issues, so the results cannot be generalized on the female population. It is worth noting that this study provides an insight that recreational weight training might alter shoulder biomechanics, whereas future investigation on shoulder kinematics of RWL would be valuable in this respect. Correlational research is also recommended to explore the relationship between antagonistic muscle imbalances in RWL and shoulder injuries.

5. Conclusion

Weightlifting training increases the strength of shoulder adductors and internal rotators. Therefore, the restoration of a normal concentric abductor/adductor and external/internal rotator strength ratios may reestablish the muscular balance of shoulder complex and prevent its recurrent injuries.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

No conflicts of interest were declared with respect to the research.

Acknowledgments

The authors acknowledge the financial support of the Taif University Researchers Supporting Project number (TURSP-2020/82), Taif University, Taif, Saudi Arabia. We also thank Dr. Maher A. Mahdi, associate professor, English Department, Helwan University, Egypt (mahermahdi@gmail.com), for his help with English language editing and revision of this article.

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Hindawi
Applied Bionics and Biomechanics
Volume 2022, Article ID 5165781, 8 pages
https://doi.org/10.1155/2022/5165781

Research Article

Shoe Bending Stiffness Influence on Lower Extremity Energetics in Consecutive Jump Take-Off

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Received 9 April 2022; Accepted 13 May 2022; Published 29 May 2022

Academic Editor: Qichang Mei

Objective. This study examined the influence of shoe bending stiffness on lower extremity energetics in the take-off phase of consecutive jump. *Methods*. Fifteen basketball and volleyball players wearing control shoes and stiff shoes performed consecutive jumps. Joint angle, angular velocity, moments, power, jump height, take-off velocity, take-off time, and peak vertical ground reaction force data were simultaneously captured by motion capture system and force platform. Paired *t*-tests were performed on data for the two shoe conditions that fit the normal distribution assumptions, otherwise Wilcoxon signed-rank tests. *Results*. There are significant differences ($P < 0.05$) in take-off velocity and take-off time between stiff and control shoe conditions; the stiff shoes had faster take-off velocity and shorter take-off time than control shoes. There was no significant difference between two conditions in jump height ($P = 0.512$) and peak vertical ground reaction force ($P = 0.589$). The stiff shoes had significantly lower MTP dorsiflexion angle and greater joint work than the control shoes ($P < 0.05$). The MTP range of motion and maximum angular velocity in stiff shoe condition were significantly lower than those in control shoe condition ($P < 0.01$). However, there are no significant differences between two conditions in kinetics and kinematics of the ankle, knee, and hip joint. *Conclusions*. The findings suggest that wearing stiff shoes can reduce the effect of participation of the MTP joint at work and optimize the energy structure of lower-limb movement during consecutive jumps.

1. Introduction

In basketball and volleyball, jumping is important and frequently executed which can be the determining factor for the outcome of a game [1, 2]. The repetitive and rapid jumps were required for rebound and block movements in basketball [3]. The previous study suggests that compared to a single jump, the consecutive jump is closer to realistic competition and provides more meaningful information to sports trainers [4]. Therefore, improving the consecutive jump ability appears necessary for basketball and volleyball players.

Previous studies have focused on improving the ability to jump through training methods [5, 6]. Markovic and colleagues [7] suggested that plyometric training could promote the use of the elastic energy and neural response benefits during the stretch-shortening cycle. Struzik and Zawadzki found that the take-off velocity is related to the stiffness of the legs, and the legs with higher stiffness have better take-off velocity performance [8]. Studies have also found a positive correlation between the take-off velocity and the MTP joint stiffness in the consecutive jump [9]. Faster take-off velocities shorten the time to reach the highest point, which makes the athlete more competitive in the race [3]. However, some studies have found that changes in footwear can affect the biomechanical characteristics [10] and jump performance. Brizuela and colleagues [11] found that increased ankle support in high-top shoes reduces ankle valgus range but increases shock to the body and reduces jumping ability.

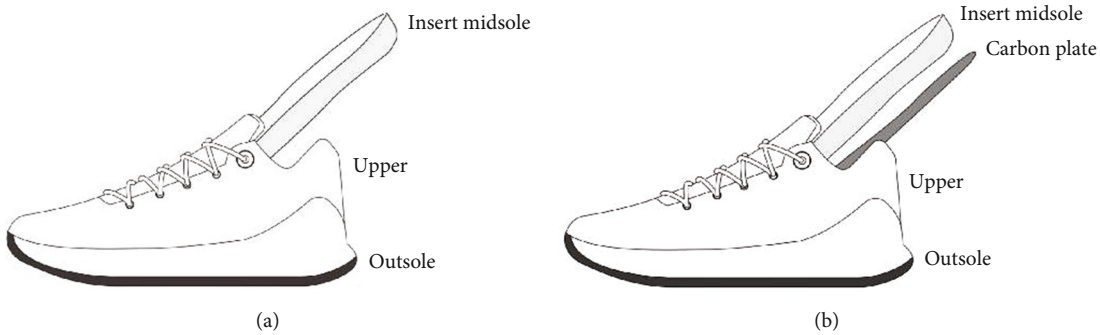

Figure 1: Schematic diagram of shoe conditions: (a) control shoe; (b) stiff shoe.

The bending stiffness of the shoe midsole has been suggested to be a direction to influence jump performance [12, 13]. One study found that MTP joint has no energy generation but absorbs large amounts of energy during take-off [14]. When increasing the midsole stiffness, a stiffer midsole would minimize the energy loss at the MTP joints, it significantly optimized the performance of the lower extremities [12]. A similar conclusion was found in another study, which found that the jump height of shoes with medial and lateral plates was higher than that of only medial plate or without it [13].

Moreover, a previous study suggested that increasing longitudinal bending stiffness of the midsole can reduce the muscle activity required to perform negative work, resulting in overall improved running economy [15]. Tinoco et al. [16] indicated that the stiffer midsole can effectively compensate for the decline in jump performance caused by fatigue.

However, the effect of bending stiffness was inconsistent between studies with different plates and types of jump. The research suggested that increasing the stiffness from flexible to the stiff conditions would not induce a beneficial effect on jump height, suggesting that the height of a single jump is not sensitive to shoes with minor differences in the bending stiffness [17]. Furthermore, extremely high bending stiffness may increase the risk of injury. High bending stiffness cycling shoes (SH-M220, Shimano, Osaka, Japan) have been shown to generate more discomfort in nonprofessional cyclists and aggravate disease in the metatarsal area, as indicated by the higher peak plantar pressure [18]. Consequently, the limited MTP flexion may be the plausible reason to increase the plantar pressure, which leads to aggravate metatarsalgia or ischaemia syndromes [18]; it also suggested that extremely high bending stiffness was not suitable for nonprofessional players.

Most studies on shoe bending stiffness are limited to single jumps and the effect on the lower extremities during the consecutive jumps. Rebounding and blocking in basketball often require repetitive and quick jumps [3]. The consecutive jump is considered to be closer to the realistic competition and can provide more meaningful information to the sports trainers than the single jumps [4]. Consecutive jumps can represent the explosive power of the lower body [19]. Furthermore, there are some biomechanical differences between single CMJ and consecutive jump. When comparing the two movements, consecutive jumps showed higher MTP and ankle extension angular velocity. The ankle, knee extension power, and knee extension moment were greater in consecutive jumps [2]. Therefore, the effect of midsole bending stiffness on consecutive jump and lower-limb biomechanics needs to be further explored.

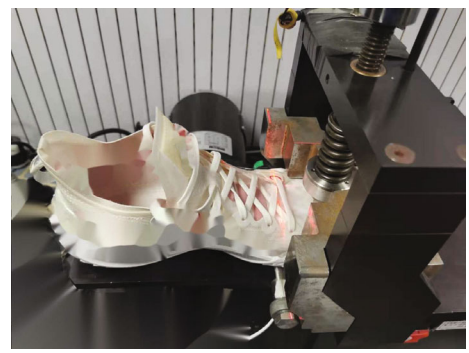

Figure 2: Shoe bending stiffness tester.

Athletes and footwear manufacturers have long been interested in the effects of shoes on jump performance [20]. Previous studies on the effect of shoe bending stiffness on the lower limb in consecutive jumps are limited. Moreover, in consecutive jumps, the effect of shoe midsole stiffness on lower extremity chain biomechanics, jump height, or take-off velocity remains unclear. The objective of the study is to explore the influence of different bending stiffness of the midsole on jump performance and biomechanical characteristics on lower extremities in consecutive jumps. It is expected that wearing higher bending stiffness shoes limits the range of motion (RoM) and angular velocity in the MTP joint and at the same time increases the RoM in the ankle and knee joints and joint energetics and jump height performance.

2. Materials and Methods

2.1. Shoe Conditions. Two conditions of shoes (stiff and control) were used in this study. The control shoe was the commercially available model for professional basketball players (ABAS011, Li-Ning, Beijing, China), which had a removable midsole (i.e., combined the insole and midsole) (Figures 1(a) and 1(b)). The stiff shoe condition was identical to the control shoe, except that there is a full-length carbon plate under the removable midsole, so that it lay between the midsole and the outsole (Figure 1(b)). This is thought to minimize

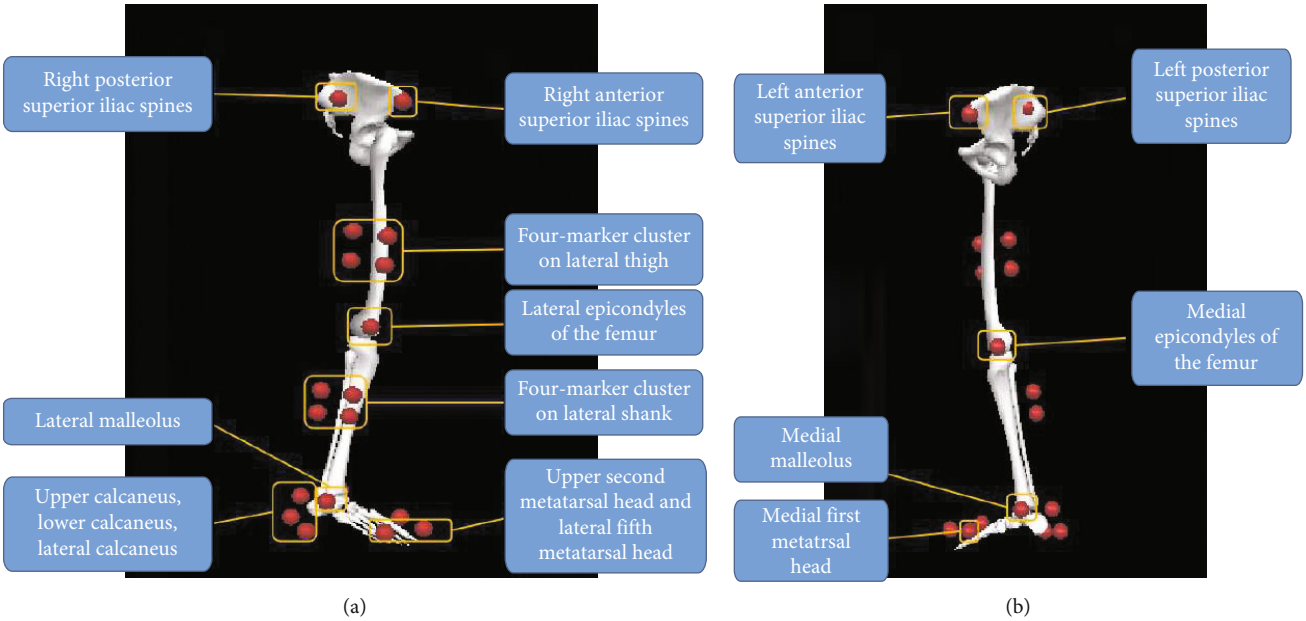

Figure 3: Reflective markers scheme: (a) right view; (b) left view.

discomfort and not to damage the shoe construction, which could be the contributing factors to jump performances and movement mechanics. The forefoot area of the shoe was fixed by the toe cap fixture, and the forefoot of the shoe was flexed from 0 degree (horizontal) to 45 degrees at 70% of the shoe length in alignment with the bending axis of the mechanical flexion tester (F911-85, ASTM, West Conshohocken, USA) (Figure 2). A total of 65 flexion trials were performed for each shoe condition, and the average value was taken from the last five trials to represent the bending stiffness of the control shoe and the stiff shoe.

2.2. Participants. A priori power analysis was calculated by G∗power (version 3.1.9.7; Heinrich Heine University, Germany) with a power of 0.8, indicating that a minimum number of 15 participants were required. Therefore, we recruited 15 male collegiate basketball or volleyball players (age = 21.2 ± 1.3 yrs; height = 176.7 ± 3.5 cm; body mass = 73.4 ± 5.6 kg; shoe size = 9 US) with 5.5 ± 1.2 yrs of experience in basketball or volleyball for this research. The dominant leg of all participants is the right leg, the way to distinguish the dominant leg is to instruct the participant to kick the ball at 4 m ahead, and if the participant kicks the ball with the right foot, then the right leg is defined as the dominant leg [21]. All participants have no lower extremity injuries, at least in the last six months. The experimental procedure was approved by the Li Ning Institutional Ethics Committee, and all participants signed informed consent.

2.3. Procedure. On arrival, the participants were briefed with the project information and signed an informed consent form. We performed anthropometric measurements including height, weight, standing touch height, foot length, and foot width. 22 reflective markers with a radius of 7 mm are distributed on the hip (four markers), right thigh (four-marker cluster), right knee joint (two markers), right shank (four-marker cluster), right ankle joint (two markers), and right foot (six markers) [2] (refer to Figure 3 for the specific location of markers).

Participants warm up with five-minute treadmill run at a personal comfortable pace, followed by self-administrated stretches and some jumps [22].

The participants were asked to put on standard socks and test shoes, which were randomly selected. At the start of consecutive jumping task, participants were asked to place right leg stand on the force platform and the left leg on the surrounding floor. Participants performed five consecutive jumps in a row without an obvious pause after each landing and require to immediately start the next jump [23]. They were required to keep the right foot on the same force platform during five consecutive jumps, and the left foot was not in contact with the force plate. A period of 120 s rest after each trial completes a shoe condition after successfully collecting valid data for 3 times consecutive jumps.

All athletes performed consecutive jump sessions. Countermovement jump is commonly used to assess lower body explosiveness and jumping performance in sports. It is also a key movement in biomechanical studies related to basketball shoes [13, 24–26]. All experimental data were simultaneously captured by an 8-camera Vicon system (200 Hz, Oxford Metrics Ltd, Oxford, UK) and a 3D force plate (1000 Hz, AMTI, Watertown, USA). The collected data included lower extremity joints' angle, angular velocity, RoM, moment, power, work, take-off velocity, jump height, take-off time, and GRF data.

2.4. Data Processing. The force data and marker trajectory data of the participants in the experiment were collected and recorded synchronously by operating Vicon Nexus software (Oxford Metrics Ltd, Oxford, UK). After the marker naming process, export the file to Visual 3D software (C-Motion Inc., Germantown, USA) to calculate and output all the required

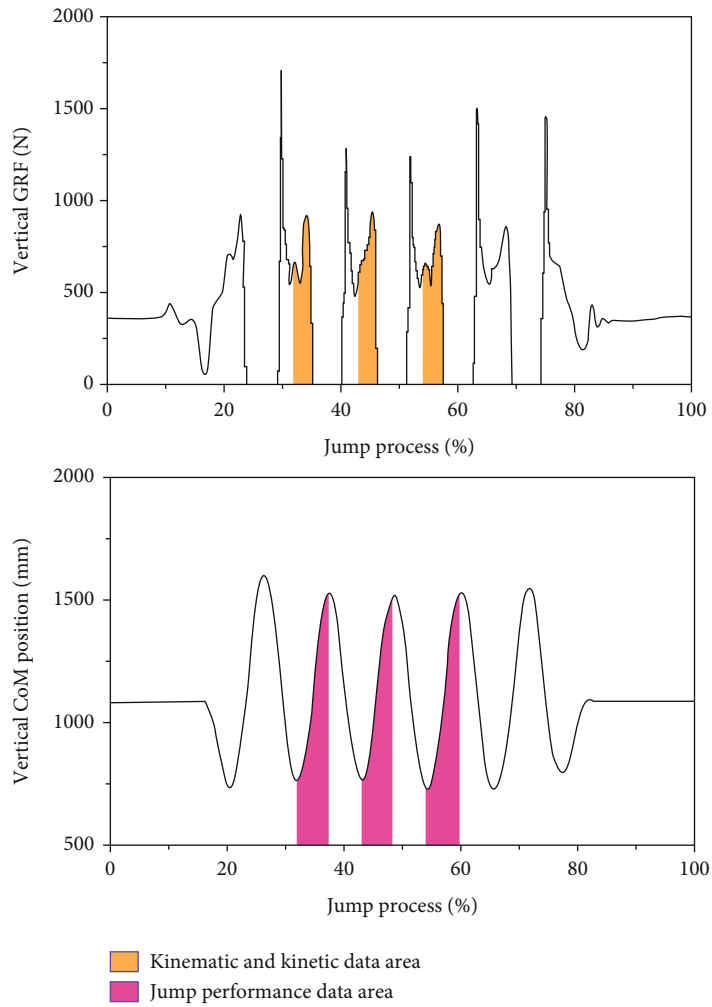

Figure 4: Data analysis area in consecutive jump.

Table 1: Shoe bending stiffness.

Variables	Control shoe	Stiff shoe
Shoe bending stiffness (Nm/°)	0.297	0.366

indicators. The kinematic data were processed with a 12 Hz cut-off Butterworth fourth-order low-pass filter [27]. The take-off period of kinetics and kinematics is defined as the time from the lowest midpoint of the line connecting the two posterior superior iliac spines (CoM) to the moment when the toes lift off the ground (the vertical GRF first drops to 10 N) [23, 28] (Figure 4). The take-off period of the jump performance is the period from the lowest to the highest point of CoM (Figure 4). The jump height calculation method is the difference between the highest point of CoM after take-off and CoM when standing still [29, 30]. The take-off velocity is calculated with reference to the upward speed of CoM after the feet leave the ground [31]. Joint angle, angular velocity, RoM, moment, power, and work are calculated by Visual 3D software. The moment, power, and work are calculated using the inverse dynamic model method [12, 13, 32] and standardized by body height (BH) and body weight (BW). The GRF data were standardized by body weight (BW). The zero degree of joint was defined in the static standing position. Hip flexion, knee extension, ankle dorsiflexion, and MTP dorsiflexion were uniformly defined as positive values.

2.5. Data Analysis. Considering that the first jump of the consecutive jump is a single jump in nature and different from the rest of the trials, only the second to fourth jump trials were extracted for subsequent analysis (Figure 4). Data normality was firstly examined with the Shapiro-Wilk test. Paired t-tests were performed on jumping performance, kinematics, and kinetic data for the two shoe conditions that fit the normal distribution assumptions, otherwise Wilcoxon signed-rank tests. Data were analyzed with SPSS software (SPSS 22.0, SPSS Inc., Chicago, USA). The significance level was set at $\alpha = 0.05$. The effect size result was interpreted as follows: the range of small effect is 0.2 to 0.5, medium effect is 0.5 to 0.8, and large effect is more than 0.8 [33].

Table 2: Jump performance and GRF variables (mean ± SD).

Variables	Control shoe	Stiff shoe	T/Z	P	Effect size
Take-off velocity (m/s)	2.68 ± 0.15	2.74 ± 0.17	-2.85	*0.013*	0.74
Jump height (BH)	0.28 ± 0.02	0.28 ± 0.02	0.67	0.512	0.17
Peak GRF (BW)	1.30 ± 0.35	1.32 ± 0.28	0.54^{Z}	0.589	0.00^{a}
Take-off time (s)	0.28 ± 0.02	0.27 ± 0.02	2.19^{Z}	*0.028*	0.36^{a}

[a]Wilcoxon signed-rank test was performed using r, otherwise paired t-test was performed using Cohen's d. Z represents the Z-value, otherwise it is the T-value. Italic numbers indicate significant difference between two conditions.

3. Results

3.1. Shoe Bending Stiffness. Through measurement, the bending stiffness of the control shoe is 0.297 Nm/°, and the bending stiffness of the forefoot of the hard-soled shoe is 0.366 Nm/° (Table 1).

3.2. Jump Performance and GRF Variables. The take-off velocity was significantly faster in the stiff shoe condition ($P < 0.05$, $d = -2.85$, medium effect); the take-off time of the stiff shoe condition is significantly shortened ($P < 0.05$, $r = 2.19$, small effect) (Table 2).

3.3. Kinematics and Kinetics of the MTP, Ankle, Knee, and Hip Joints. The stiff shoe condition had significantly lower MTP joint dorsiflexion angle ($P < 0.05$, $d = 2.41$, medium effect), RoM ($P < 0.01$, $d = 3.53$, large effect), and maximum angular velocity ($P < 0.01$, $d = 6.94$, large effect), and the work was greater than control shoe ($P < 0.05$, $d = 2.23$, large effect) (Table 3).

No significant differences between two conditions were found in hip, knee, and ankle joints (Table 3).

4. Discussion

This study investigated the biomechanical effects of consecutive jumps with two different conditions of forefoot bending stiffness as a reference for jumping-related sports. The experimental results supported part of our hypothesis that the stiff shoe condition restricted the RoM and the joint angular velocity of the MTP joint during the take-off period. But there is no significance in kinematics and kinetics of ankle, knee, and hip joint, as well as jump height.

The jump height results did not support our hypothesis, which is also different from Stefanyshyn and Nigg's findings [14]. The authors suggested that the stiffer shoes reduce the energy absorbed from the MTP joint, and the rest of energy would improve about 3.5 cm height (70 kg mass body). Some other studies also found no significant differences between stiff and control conditions in lay-up movement [22] and running vertical jumps [17]. One possible reason is that the actual difference in stiffness between the two shoes is too small to generate the significant improvement showed in Stefanyshyn and Nigg's study (energy improvement= mass × height × gravity = 70 × 3.5/100 × 9.81); the experiment of Stefanyshyn and Nigg's [12] research increased the forefoot stiffness from 0.04 Nm/° to 0.25 Nm/°; our conditions only compared the difference between 0.297 Nm/° and 0.366 Nm/°, so it is not difficult to understand: there are significant differences in MTP joint work, but insufficient changes at the MTP joint to significantly alter athletic performance. However, according to our results, the stiff shoes significantly improved the take-off velocity and shortened the take-off time, which are considered to be positive performance benefit in sports [3]. Faster take-off velocity can help an offensive player disrupt the defender's timing, create a foul, and then take a shot [34]. This is similar to previous studies, who also found that higher forefoot bending stiffness improved sprint and cut performances [13, 17].

As hypothesized, several differences in MTP kinematics were found. These changes are in line with the previous research [12, 14]. Increasing MTP joint stiffness reduced MTP joint maximum dorsiflexion angle and RoM, limited the angular velocity of MTP joint dorsiflexion, and minimized dissipated energy, which is related to improved jump velocity. These confirm our previous first hypothesis. Joints with greater angular velocity and loading represent greater range of motion and muscle-ligament strain in rapid push-off, which may suggest better take-off performance [9]. It should be noted that it would also be considered potentially modifiable risk factors for lower extremity injuries [35, 36]. At the instant before toe-off the ground, the MTP plantarflexion angular velocity in the stiff shoe condition is higher than that in the control condition. Although there is no statistical difference, it can be explained to a certain extent that a shoe with high stiffness might restore the forefoot to its original position faster [37].

From the test results, there is no significant difference in the kinematics and kinetics of the hip, knee, and ankle joints, which does not agree with some literatures. The results of Zhu and colleagues [22] showed that a stiff midsole significantly improved ankle RoM, maximum power, energy absorbed, and energy produced. Another study also found that stiff shoes can regulate the biomechanical properties of the ankle joint [38]. They believe that the stiff shoe changes the force application point to the position where the toe region is in contact with the ground, resulting in the occurrence of a complementary change of the lower extremity joint kinematic chain. No such obvious changes determined in this paper may be due to the small change in the stiffness of the midsole [17], and it is also possible that compared with a single jump (MTP angle is zero at the beginning), after the buffer stage of the last landing, the forefoot has been bent at the beginning of the take-off stage, resulting in a small change in GRF application point.

Through this experiment and combined with previous studies on vertical jumps [12, 22], the effect of shoe bending stiffness on the upward jump is concentrated on the MTP

Table 3: Kinematics and kinetics of the MTP, ankle, knee, and hip joints during the take-off phase (mean ± SD).

Variables	Control shoe	Stiff shoe	T/Z	P	Effect size
MTP					
Max. angle (°)	36.96 ± 2.88	35.14 ± 2.29	2.41	*0.030*	0.62
Min. angle (°)	28.46 ± 3.34	28.62 ± 2.30	-0.25	0.808	0.06
RoM (°)	8.50 ± 1.84	6.52 ± 2.19	3.53	*0.003*	0.91
Max. angular velocity (°/s)	164.97 ± 44.72	129.36 ± 33.96	6.94	*0.000*	1.79
Min. angular velocity (°/s)	−252.29 ± 75.44	−272.50 ± 74.00	2.02	0.064	0.52
Max. moment (Nm/BW·BH)	0 ± 0.02	0 ± 0.02	1.54^{Z}	0.125	0.56^{a}
Min. moment (Nm/BW·BH)	−0.17 ± 0.09	−0.17 ± 0.05	0.10	0.923	0.03
Max. power (W/BW·BH)	0.31 ± 0.13	0.27 ± 0.13	1.40	0.183	0.36
Min. power (W/BW·BH)	−0.34 ± 0.19	−0.21 ± 0.15	1.51^{Z}	0.132	0.55^{a}
Work (J/BW·BH)	−0.01 ± 0.01	0 ± 0.01	2.23^{Z}	*0.026*	0.97^{a}
Ankle					
Max. angle (°)	28.09 ± 5.71	28.15 ± 5.94	-0.11	0.911	0.03
Min. angle (°)	−39.08 ± 6.46	−39.58 ± 6.82	0.84	0.414	0.22
RoM (°)	67.17 ± 6.56	67.73 ± 6.83	-0.86	0.402	0.22
Max. angular velocity (°/s)	−775.61 ± 108.52	−775.85 ± 117.93	0.02	0.982	0.01
Max. moment (Nm/BW·BH)	0.02 ± 0.02	0.01 ± 0.02	0.92	0.371	0.24
Min. moment (Nm/BW·BH)	−0.90 ± 0.22	−0.89 ± 0.17	-0.21	0.834	0.06
Max. power (W/BW·BH)	6.11 ± 2.16	6.03 ± 1.50	0.20	0.845	0.05
Min. power (W/BW·BH)	−0.34 ± 0.34	−0.35 ± 0.28	0.51^{Z}	0.609	0.03^{a}
Work (J/BW·BH)	0.46 ± 0.14	0.48 ± 0.10	-0.39	0.701	0.10
Knee					
Max. angle (°)	−16.40 ± 22.03	−18.07 ± 11.62	0.34^{Z}	0.733	0.26^{a}
Min. angle (°)	−100.97 ± 19.16	−102.17 ± 20.88	0.72	0.486	0.19
RoM (°)	78.30 ± 19.75	83.57 ± 16.89	-1.21	0.247	0.31
Max. angular velocity (°/s)	879.54 ± 111.67	868.46 ± 112.65	0.84	0.414	0.22
Max. moment (Nm/BW·BH)	1.34 ± 0.33	1.34 ± 0.34	0.04	0.973	0.01
Min. moment (Nm/BW·BH)	−0.23 ± 0.12	−0.23 ± 0.11	0.18	0.862	0.05
Max. power (W/BW·BH)	8.79 ± 1.65	8.59 ± 1.44	0.76	0.461	0.20
Min. power (W/BW·BH)	−3.49 ± 2.02	−3.64 ± 1.79	0.29	0.777	0.07
Work (J/BW·BH)	0.79 ± 0.212	0.83 ± 0.23	1.02^{Z}	0.306	0.26^{a}
Hip					
Max. angle (°)	78.85 ± 22.40	79.84 ± 22.43	-0.52	0.609	0.14
Min. angle (°)	18.16 ± 19.62	17.16 ± 14.28	1.25^{Z}	0.211	0.21^{a}
RoM (°)	55.55 ± 16.33	60.15 ± 15.89	-1.75	0.101	0.45
Max. angular velocity (°/s)	−446.32 ± 83.70	−454.65 ± 76.96	0.57^{Z}	0.580	0.15^{a}
Max. moment (Nm/BW·BH)	0.26 ± 0.13	0.30 ± 0.16	-1.25	0.234	0.32
Min. moment (Nm/BW·BH)	−1.20 ± 0.23	−1.29 ± 0.24	1.42	0.178	0.37
Max. power (W/BW·BH)	3.50 ± 0.83	3.76 ± 1.10	-1.97	0.069	0.51
Min. power (W/BW·BH)	−2.50 ± 1.36	−3.03 ± 1.47	1.79	0.095	0.46
Work (J/BW·BH)	0.37 ± 0.16	0.39 ± 0.23	-1.00	0.333	0.26

[a]Wilcoxon signed-rank test was performed using r, otherwise paired t-test was performed using Cohen's d. Z represents the Z-value, otherwise it is the T-value. Italic numbers indicate significant difference between two conditions.

joints, and the influence on the hip and knee joints is relatively small.

There are some limitations in this study. There are only two conditions in this study. If there are more stiffness carbon plates with larger absolute differences between shoe conditions, the systematic changes can be established for a deeper interpretation. Moreover, only the collegiate basketball and volleyball team players were recruited; the professional athletes would be used to evaluate the shoe bending effect as indicated by consistent jump movements between trials in professional athletes.

5. Conclusions

During the five consecutive jumps, the longitudinal midsole stiffness would significantly improve the take-off speed and shorter time to reach the highest point but did not result in the absolute difference in jump height and lower-limb joint kinematics. These results suggest that wearing stiff shoe can reduce the effect of MTP joint participation in work and optimize the energy structure of lower-limb movement during consecutive jumps.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Authors' Contributions

Sheng-Wei Jia and Fan Yang contributed equally to this work and should be considered co-first authors.

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