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RESEARCH ARTICLE

Deep Learning

Athlete body power and strength estimation using skeleton point cloud

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Abstract: Vertical jump assessment is one of the most frequently used techniques to evaluate lower limb strength and power in the context of strength and conditioning. Countermovement jump (CMJ) and squat jump (SJ) have been recognized as the most valid and reliable vertical jump tests to assess body power and strength. The traditional method requires professional involvement and equipment for parameter assessment. In the context of college athletes, it is not practical to acquire direct supervision from coaches and use laboratory-based equipment such as force plates. Hence, the main objective of this study is to reduce the physical involvement in the traditional method by developing a system to identify lower body power and strength, which can be handled at an athlete's own pace. Thus, we propose a single camera system that captures athlete skeleton joint variation from the lateral view to identify the accuracy of CMJ and SJ along with measurements for power, maximum jump height, reactive strength index, and ground reaction force. These performance parameter values are measured using a rule-based model developed with motion equations and skeleton joint variations. The biomechanics of the exercises are identified based on the clinically accepted jump protocol. The experimental results show that the system identifies athlete biomechanics with an accuracy of 91.7% for CMJ and an accuracy of 95.8% for SJ. Also, the system measures maximum jump height with a standard error of 0.88 cm.

Keywords: Biomechanics, countermovement jump, moveNet, Skeleton point cloud, Squat jump.

INTRODUCTION

Lower body strength and power identification provide valuable insights into different capacities such as an athlete's movement coordination and timing. This information can be used in connection with the art of coaching to maximize athlete training program effectiveness. But training an athlete's power and strength to improve his/her sport performance is a challenging aspect of coaching. In the traditional strength and power identification process, sports instructors offer expert advice, monitoring correctness of counter movement jump and squat jump along with parameter measurements such as maximum height jumped by the athlete. In the local context, the most fundamental method of identifying athletes' performance is the jump and reach test. However, due to inability to take accurate and reliable measurements, several researchers have proposed laboratory and field-based methods such as force plates and contact mats, to replace the use of jump and reach test for measuring athletes' power and strength. However, many athletes tend to be involved in sports without identification of their body capacities due to issues such as difficulty in acquiring expensive equipment and obtaining the involvement of domain

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experts (Velloso *et al.*, 2013). If athletes are not routinely assessed to identify body powers, their performance capacities will not be identified properly. Even though athletes try to use limited resources, it is crucial to perform strength and power jumps in clinically accepted procedures because jumps without proper guidance have a consequential impact on jump adherence and technique (O'Reilly *et al.*, 2017). With the increasing availability of portable devices such as laptops and mobile phones with sensing features, studies have proposed many self-assessment approaches with use of wearable and nonwearable sensors. Human action recognition (HAR) has attracted the attention of research communities in the computer vision area in recent years. Use of action recognition has made tremendous progress in the strength and conditioning context, such as AI based physical fitness training, self-assessment of body capacities, and sport-specific movement analysis. The introduction of low-cost depth sensors like Microsoft Kinect and Orbbec Astra Pro and pose estimation methods such as the moveNet model have made the use of human action recognition easier. The primary motivation for this research study is to propose a solution for athletes to routinely self-assess their lower body power and strength along with feedback for the correctness of counter movement jump (CMJ) and squat jump (SJ) by using a full body tracking approach. The goal of this research is to reduce the professional involvement for physical inspection in the strength and power estimation of athletes and minimize the subjectiveness that happens when taking measurements.

Related work

Recent technological advances have sparked interest in the research community to use different technologies in the strength and conditioning context (Gallagher & Heymsfield, 2023). Much research has been conducted and many commercial applications developed to provide virtual physical fitness training. Some of the physical fitness solutions that are built without any external sensor hardware are Fitness Expert, Adidas micoach, Abs & core, AndAndo (Kranz *et al.*, 2013). However, there are only a limited number of studies conducted in self-assessment of an athlete's body capacities. Suchomel *et al.* (2016) have presented that an athlete's muscular strength is highly correlated to running, superior jumping and other sport specific performances. The related work of our study is classified into two categories. Those are the studies related to an athlete's biomechanical identification and work related to performance parameter identification of athletes.

Performance parameter identification

In the local context, the most fundamental method of identifying an athletes' performance is the jump and reach test. However, due to inability to take accurate and reliable measurements in this method, several researchers have proposed laboratory and field-based technologies. In a study, Beckham *et al.* (2012) discussed the identification of an athlete's strength using a force platform by considering flight time and net pulse as the performance parameters. Even though force plates allow the athletes to collect high-quality data such as maximal strength, rate of force development, and explosive performance, they are complex devices, which makes it difficult to master their use in field-based assessments. Whitmer *et al.* (2015) have proposed contact mats to estimate athletes vertical jump height. The contact mat calculates the vertical jump height similarly to a force plate, which is commonly used in laboratory settings. Glatthorn *et al.* (2011) have pointed out that the validity of contact mat measurement degrades due to the fact that feet are not directly in contact with the sports surface. Hence, they have proposed optjump photocells, which use the athlete's jump flight time to calculate jump height. An athlete's device contact time is estimated using the time where the laser beam is broken and the flight time as the period where the laser beam is broken. However, due to the difficulty in handling the proposed devices in the field, many studies have focused on inertial sensors. Wearable and minimally invasive sensors have seen a surge in popularity in recent years, as they can provide useful information for athletes' functional evaluation in sports. Risk analysis and performance enhancement can be refined through wearable devices in sports applications (Franchini *et al.*, 2022). A study has proposed a method to predict jump heights, including jumps with simple rotations using a single inertial measuring unit (IMU) (King & Paulson, 2007). In order to track a full body motion, it is required to use several inertial sensors. Without the use of markers on the human body, it is now possible to analyze the motions of humans in a natural context of activity. The development and availability of accessible and easy-to-use motion capture technologies are aided by these new motion analysis approaches (King & Paulson, 2007). According to the literature, most of the studies have proposed solutions to identify maximum jump height and ground reaction force (GRF). Mascherini *et al.* (2019) have concluded that several parameters should be evaluated at the same time as vertical jump height in order to have a correct functional assessment of athletes and healthy non-sporting subjects.

Biomechanical identification

Biomechanics is the study and science of the way in which the structure of biological creatures responds to exterior forces and stimuli (Lu & Chang, 2012). Pueo (2016) has proposed a method that uses high tech cameras that can visualize an athlete in 3D space. Chang *et al.* (2007) have used a 3-axis accelerometer incorporated into a workout glove to detect hand movement of weight-lifting athletes. In this approach, the accuracy of the exercise is not considered. The work is limited only to recognizing the exercise based on highest likelihood. In a study, Lu *et al.* (2021) have proposed a method to recognize the human lower limb vertical jump phases using bidirectional LSTM and convolutional LSTM. This work limits the vertical jump phase based on previously trained jump phases. Abdur Rahman *et al.* (2013) have proposed a multimedia interactive therapy environment for children having physical disabilities. The study focuses only on elbow joint variation and compares angle calculation with a conventional device called a goniometer. Ding *et al.* (2015) have developed a platform for Free-weight Exercise Monitoring using RFIDs, which determines what exercise a user is undertaking based on the frequency of the weight's movements. Even though the proposed work identifies the free weight exercise, this work fails to identify the correctness of the kinematics with time. The aforementioned methods have focused on movement recognition. Several studies have used skeletal point tracking to evaluate certain stances used in sports like taekwondo (Fernando *et al.*, 2024) and badminton (Krishnaram *et al.*, 2024). However, a mechanism for identifying the biomechanics of counter movement jump and squat jump using self-assessment technologies has not yet been explored. With the invention of the depth camera, clear information on 3D structural views was received. Cameras with depth sensors such as Microsoft Kinect, RealSense, and Orbbec Astra Pro have been used for human skeleton joint tracking (Farooq & Won, 2015). Some studies show the use of multiple cameras for motion capture, particularly useful in sports and neurorehabilitation settings (Bianchi *et al.*, 2023). Sapinski *et al.* (2019) have proposed a method to recognize seven basic emotional states utilizing body movement tracked using Microsoft Kinect. Lai *et al.* (2017) have used multiple acceleration sensors and gyroscopes to identify body motion patterns. Bajpai & Joshi (2021) have proposed a model named moveNet which is a predictive 14 neural network that identifies skeleton joints of humans. Hence, we intend to evaluate which method out of the moveNet model and Orbbec camera is best suited for tracking counter movement jump and squat jump, and provide a solution to assess lower body power and strength at athlete's own pace, including both biomechanics and performance variables.

MATERIALS AND METHODS

As mentioned in the previous section, there are no studies that have been conducted using skeleton tracking to carry out the biomechanical assessment and performance parameters simultaneously to estimate lower body power and strength of athletes. One of the main objectives of this study is to identify the correctness of countermovement jump and squat jump by using a biomechanical model in combination with the quantitative measurements for power, maximum jump height, ground reaction force, and reactive strength index identified, using a model named performance parameter model.

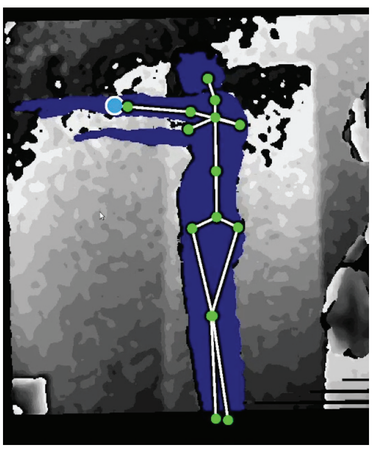
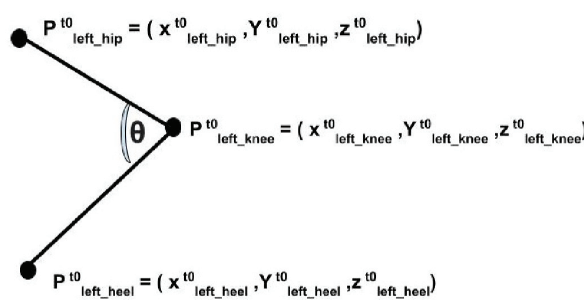
Identify clinically accepted jump biomechanics and parameters

Initially, the clinically accepted procedure of estimating athlete body power and strength was obtained by referring to the journals suggested by domain experts. According to Markovic *et al.* (2004), countermovement jump and squat jump have shown high reliability and validity in testing lower limb performance. The jump protocol presented by Petrigna *et al.* (2019) was taken as the clinically accepted procedure for a countermovement jump and a squat jump. These instructions are transformed into an approach which uses the skeleton joint data of an athlete. Table 1 represents the derived transformations. The left side of the table contains the clinical procedure of countermovement jump and the right side represents the procedure in terms of skeleton joint variation.

Skeleton tracking technology selection

According to the literature, depth cameras and pose estimation models have shown a high reliability for markerless motion capturing applications (D'Haene *et al.*, 2024). In this study both the approaches are used to track countermovement jump and squat jump. The MoveNet pose estimation model and the skeleton tracking algorithm of the Orbbec astra camera was chosen to evaluate accuracy for the skeleton tracking method. The athlete's movement along the coronal plane is tracked with the variation of **x** coordinate, movement along the sagittal plane is tracked with the variation of **y** coordinate, and the movement along the transverse plane is tracked using the **z** coordinate. In order to determine the accuracy of the skeleton detection algorithm in the camera, a code was implemented to calculate the angles between the joints. After analyzing the skeleton joint angles for the movement of an athlete in the erect position (straight knees) and downward movement until the knee angles are approximately 90°, it was found that the joint values predicted from the skeleton detection algorithm in the depth camera was not consistent with the speed of the jump. Figure 1 represents the plot of left knee angle (red), right knee angle (blue) variations with time and the difference of those angles (green).

Table 1: Transformation of counter movement jump

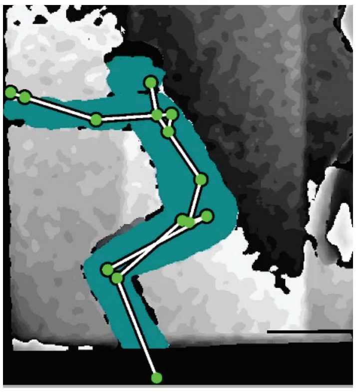
Clinical and theoretical evaluation	Skeleton point cloud mapping
Biomechanical assessment  Straight legs and spine at start time	A 3D point at tn time in i[th] joint is noted as $P_n^i = (x_n^i, Y_n^i, z_n^i)$ • Consider hip, knee, heel joint points at starting time t0 $P^{t0}_{left\_hip} = (x^{t0}_{left\_hip}, y^{t0}_{left\_hip}, z^{t0}_{left\_hip})$ $P^{t0}_{right\_hip} = (x^{t0}_{right\_hip}, y^{t0}_{right\_hip}, z^{t0}_{right\_hip})$ $P^{t0}_{left\_knee} = (x^{t0}_{left\_knee}, y^{t0}_{left\_knee}, z^{t0}_{left\_knee})$ $P^{t0}_{right\_knee} = (x^{t0}_{right\_knee}, y^{t0}_{right\_knee}, z^{t0}_{right\_knee})$ $P^{t0}_{left\_heel} = (x^{t0}_{left\_heel}, y^{t0}_{left\_heel}, z^{t0}_{left\_heel})$ $P^{t0}_{right\_heel} = (x^{t0}_{right\_heel}, y^{t0}_{right\_heel}, z^{t0}_{right\_heel})$ • Calculate angle between three 3D vectors of hip, knee, heel  A 3D point at time tn in the i[th] joint is noted as P $a = P^{t0}_{left\_knee} P^{t0}_{left\_hip}$ $b = P^{t0}_{left\_heel} P^{t0}_{left\_knee}$ $a.b = \|a\| * \|b\| * cos(\theta)$ $cos(\theta) = \frac{a.b}{\|a\| * \|b\|}$ • Calculate the angle between three 3D vectors of hip, knee, heel joints • Calculate the angle between three 3D vectors of neck

<table>
<tr><th>Clinical and theoretical evaluation</th><th>Skeleton point cloud mapping</th></tr>
<tr><td>

Biomechanical assessment

Downward movement until knee angles are flexed (approximately) 90◦

Check for the maintenance of this posture for at least 2s.



Knee angles are flexed □90◦

</td><td>

• Calculate the angle between three 3D vectors of the hip, knee, and heel joints

• Calculate the angle between three 3D vectors of knee, mid spin, neck

• Need to check whether the joint positions are fixed within the considered time.

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Parameter assessment

Start calculating the time duration between the subject's take-off (t3) and touch down (t4)

Calculate the maximum height jumped

Calculate the maximum force generated by lower limbs during landing

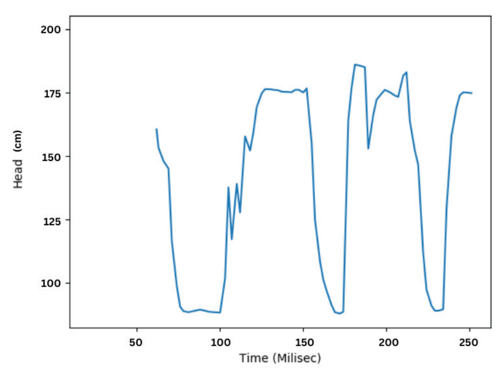
</td><td>

Process y^{t0}_{head} point coordinates of the head joint

• Identify time t2 when head joint's y values are changing

• Identify time t3 when head joint's y value is maximum

• Identify time t4 when heel joint's y values become stable



Represents the raw data of the head joint's y plane variation with time when Counter Movement Jump is performed

• Calculate the maximum force generated by using following motion equations and Newtonian law formula

Acceleration a = F / m, Velocity V = u + at, Displacement s = (1 /2)(v - u)t, Power P = FV

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Biomechanical assessment

After landing, the end position should be the same as the starting.

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Since the biomechanical assessment of the end position is similar to the starting position, the mapping identified in the starting position will be used in this phase

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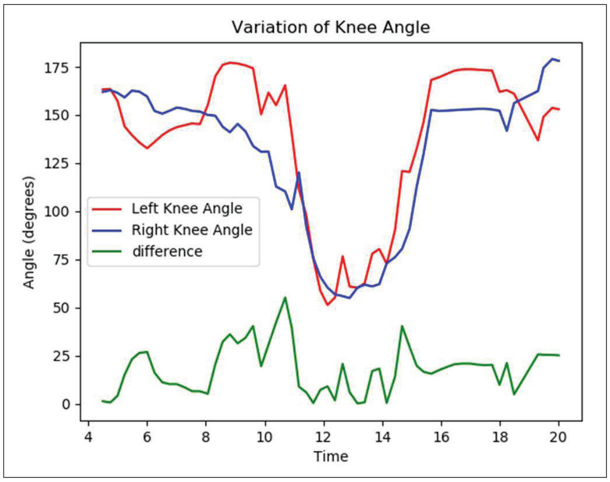


Figure 1: Variation of knee angles in low cost depth camera

Since the graphical representation showcases some higher angle differences for left and right knee angles, the moveNet pose estimation model had better accuracy. Figure 4 represents the plot of the left knee angle (red), right knee angle (blue) variations with time and the difference of those angles (green) by using the moveNet model for countermovement jump and squat jump.

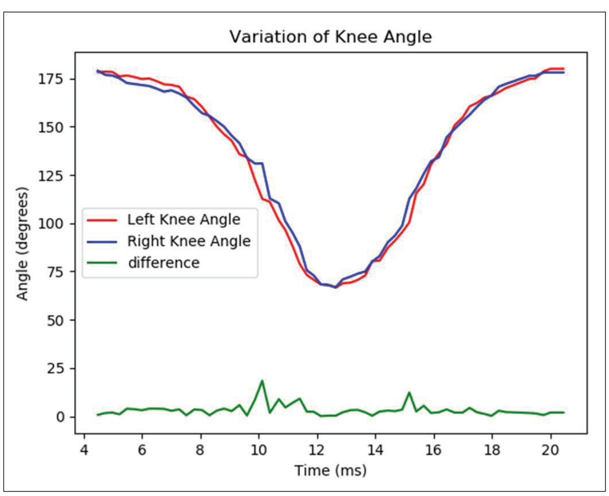


Figure 2: Variation of knee angles with time in moveNet model

The depth camera and moveNet model evaluation was conducted using an evaluation metric. The sum of all the angle differences throughout the movement is calculated using the metric. The metric, average joint difference, is defined in equation 1,

$$d_{avg} = \frac{\sum_{i=1}^{N} || \ LK_{orbec,i} \ - \ RK_{orbec,i} \ ||}{N} \qquad \ldots(1)$$

In particular, after calculating joint angles using the skeleton point cloud received from the depth camera and the moveNet model, we compared the left knee angle and the corresponding right knee angle for all frame updations N, respectively named LKorbbec, i and RKorbbec, i . And the moveNet returned a low average of joint angle differences. Hence the moveNet model was chosen for tracking the athlete's skeleton in real time.

Biomechanical model development

The rule based approach is used to construct the two models, performance parameter model and biomechanical model. The main reason for using a rule based approach is to capture the knowledge of human experts and journals in a specialized domain (sport science) and embody it within a computational model. Hence the knowledge is encoded as rules. The identified transformations are used to develop the biomechanical model. The angle between two lines in 2D space is equal to the angle subtended by the two vectors which are parallel to those lines. The angle between the two vectors a = (x1,y1) , b = (x2,y2) are calculated using the equations 2 and 3.

$$a.b \ = \ |a| \ * \ |b| \ * \ cos\ (\theta) \qquad \ldots(2)$$

$$cos(\theta) \ = \frac{a.b}{|a| \ * \ |b|} \qquad \ldots(3)$$

Performance parameter model development

Movement within sport is considered to measure the parameters quantitatively. The concept of linear motion is applied to identify the maximum height jumped by the athlete. When performing countermovement jump and squat jump, it is assumed that all parts of the athlete are moved at the same speed during flight time. Newton's second law is used to identify the power generated by the athlete. According to the theory, the acceleration of an athlete during the flight time of the two jumps is proportional to the size of the force and inversely proportional to the athlete's body mass (F = ma). The takeoff time is identified using the presence and absence of ankle lift. Since the ankle lift movement occurs along the y plane, the instance where the values of the ankle joint start to change and joint y value comes to the value initial state was used. The maximum height jumped by the athlete is calculated using a function accepting an array of values for ankle joint y plane variation, takeoff time, flight time and scale as inputs. The average of left ankle variation and right ankle variation is taken as the maximum height. The following equations are used to calculate performance parameters: *Power* = Energy/time, *Reactive strength index* = jump height/ time for jump, *Upward acceleration* = jump height / (time for jump * 2) , and *GRF* = (Upward acceleration * weight) + (weight * 9.8)

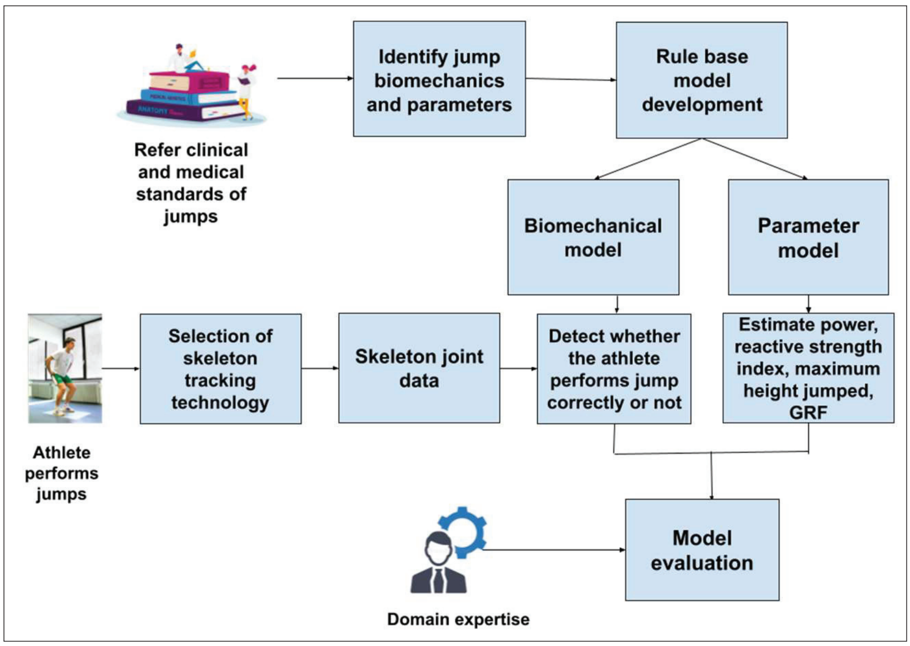


Figure 3: Overview of the research workflow

High-level research design

The proposed solution is a combination of biomechanical assessment and performance parameter assessment. These two assessments are performed by developing two rule-based models separately. The high level architecture of this study depicts the step-wise procedure of concluding the study. Finally, the two models are fine-tuned based on the feedback from domain experts. The Figure 3 represents the overview of the research workflow.

Athlete classification based on sport domain

This stage represents an application of the use of power and strength calculated from the proposed system. According to previous studies, athletes have shown different strength and power levels based on their sport domain. In this study, Kmeans clustering was used to identify whether there is a clear separation of athletes based on their strength and power values. The reason for the use of Kmeans algorithm is its adaptation to new examples and its ability to warm-start the positions of centroids.

RESULTS AND DISCUSSION

As discussed, both the biomechanical assessment and performance parameter assessment are focused in this study. The skeleton joint variation obtained from the moveNet pose estimation model is used as input for the biomechanical model and performance parameter model. When the model is executed, it continuously returns the joint values at 30+ FPS as lists for each joint updation, as shown in Figure 4 below. Each list has 17 array values representing each joint. The code outputs an athlete's video along with the correct skeleton joints.

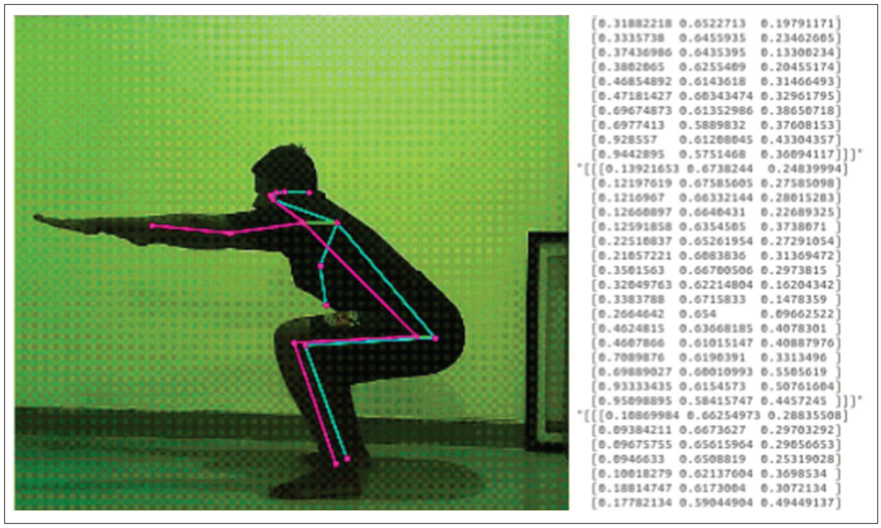
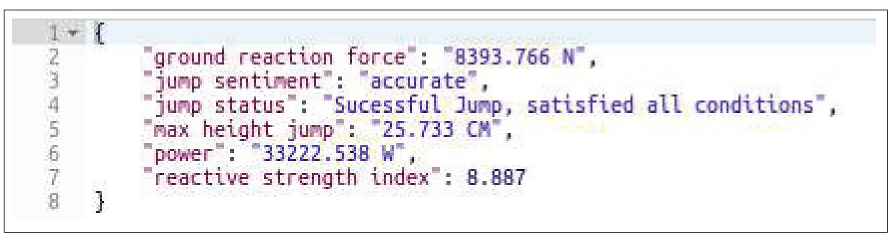


Figure 4: A snapshot of the MoveNet model outputs for CMJ running at 30+ FPS



```
{
    "ground reaction force": "8393.766 N",
    "jump sentiment": "accurate",
    "jump status": "Sucessful Jump, satisfied all conditions",
    "max height jump": "25.733 CM",
    "power": "33222.538 W",
    "reactive strength index": 8.887
}
```


Figure 5: Computational output for an athlete's counter-movement jump

Finally, the joint values received from the moveNet model are fed into the performance parameter model and biomechanical model. Additionally, the athlete's body weight needs to be taken as an input to measure performance parameters. The parameters that have been calculated are ground reaction force, maximum jump height, power, and reactive strength capacity. In addition to these parameters, jump status is identified. The computational output of a Netball player when performing countermovement jump is represented in Figure 5

The accuracy of the proposed system is identified with the involvement of domain experts. A set of subjects were evaluated as they performed the CMJ and SJ in front of the camera and the domain experts. The evaluation results obtained from the system are compared with the evaluation results of a domain expert to conclude how accurate the system output is. Domain experts observed the jump and clinically analyzed the accuracy of the jumps. Further, the strength and power measurements were taken with the help of a sport instructor. Then the results of our study were compared against the expert opinion and the model fine tuned.

Subjects

Twenty five (25) subjects including 10 male athletes (university hockey team) and 14 female athletes (university netball team), 20 - 25 years of age, were enrolled to volunteer for the model evaluation. The average age of subjects is 23.7. The selection was done with the help of a domain expert.

Jump protocol

An indoor space at the sports complex of the University of Colombo was used for experimental tests. Since the moveNet model produces only sagittal (x) plane and coronal (y) plane values, to avoid the effect from transverse (z) plane variation, the athlete was asked to perform the jumps at a predefined position where the distance between the camera and the subject was 2 m and camera was placed 65 cm above and parallel to the floor. At the beginning, the weight of each subject was measured and they were asked to warm up for 5 minutes. And then they were instructed to perform counter-movement jump and squat jump barefoot. While athletes perform jumps one after the other, the jump height was measured using a tape attached to the wall. Athletes were asked to apply some liquid in their hand and were asked to touch the wall at their maximum jump point. The difference between normal touch point and maximum touch point was taken as the ground truth for maximum jump height parameter.

Evaluation of the biomechanical model

In this research a confusion matrix-based evaluation was used to clarify the accuracy of the biomechanical model. The model was evaluated separately for counter movement jump (CMJ) and squat jump (SJ). Then the model was fine-tuned based on domain expert opinion and was re-evaluated. Subjects are binary classified based on the correctness of their jump. Thus the confusion matrix presents four possible outcomes derived by comparing model output and domain experts feedback. The following is the list of terminology used in the confusion matrix.

True Positive (TP) - the case where the model output is that subject performs the jump correctly and the domain expert confirms the subject actually does.

True negative (TN) - the case where the model output is that the subject does not perform correctly and the domain expert confirms that the subject actually does not perform correctly.

False positive (FP) - the case where the model output is that the subject performs correctly and the domain expert clarifies the subject does not perform correctly.

False negative (FN) - the case where the model output is that the subject does not perform jumps correctly and the domain expert clarifies the subject performs correctly.

The confusion matrix for CMJ and SJ of the initial evaluation, the accuracy of the biomechanical model for CMJ before fine tuning is 79.2% and the mis-classification rate is 20.8%. The accuracy of the biomechanical model for SJ before fine tuning is 83.3% and the mis-classification rate is 16.7%.

To achieve better accuracy, the biomechanical model was fine-tuned. According to the domain expert feedback, an additional rule was added to the model where it checked the forward-leaning of athletes. The confusion matrix for the fine-tuned model is represented in Table 2 and Table 3 respectively. The accuracy of the biomechanical model for CMJ after fine tuning is 91.7% (8+14) / 24*100%) and the mis-classification rate is 8.3% (1+1) / 24*100%). The accuracy of the model for SJ after fine tuning is 95.8% (10+13) / 24 * 100%) and the mis-classification rate is 4.2% (0+1)/24* 100%).

Table 2: Confusion matrix for cmj after model fine tuning

		Computational output	
		Positive (correct jump)	Negative (incorrect jump)
Domain expert opinion	Positive (correct jump)	TP = 8	FN = 1
	Negative (incorrect jump)	FP = 1	TN = 14

Table 3: Confusion matrix for sj after model fine tuning

		Computational output	
		Positive (correct jump)	Negative (incorrect jump)
Domain expert opinion	Positive (correct jump)	TP = 10	FN = 1
	Negative (incorrect jump)	FP = 0	TN = 13

Evaluation of the performance parameter model

In this research, an athlete's four parameters were identified using skeleton joint variation. Those are the power, maximum jump height, reactive strength capacity, and GRF. The maximum jump height parameter is evaluated by comparing the value given by the proposed system and the value calculated using the jump and reach test where a measuring tape was attached to the wall and the athlete was asked to touch the maximum reach point. The average standard error between the computed values and clinical methods is used to evaluate the performance parameter model. The calculated absolute standard error for jump height variable is 0.88 cm. In the performance parameter model, parameter values are estimated only if the biomechanical model detects that an athlete's jump has an accurate jump movement.

Athlete classification based on sport domain

This phase is an application of the data computed using the proposed models. All the data of athletes whose jump status was identified as correct were considered for classification. K means clustering was applied to cluster athlete data. Figure 6 represents the two clearly separated clusters. When manually analyzed, it can be seen that red spots represent the hockey players and purple spots represent the netball players.

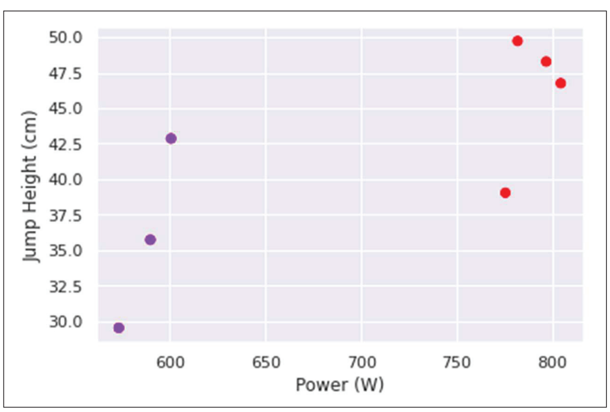


Figure 6: Classification of hockey players (red) and netball players (purple) using power and maximum jump height

According to Thomas *et al.* (2017), netball players have been classified as strong and weak based on their power and jump height values. Our study used these parameter values as a reference to classify athletes based on their parameter values calculated using our proposed solution.

Based on the available literature, this is a novel approach to identify body power and strength in athletes using skeleton tracking. A rule-based model was created to identify the counter movement jump and squat jump accuracy of athletes and to quantitatively measure power, reactive strength capacity, maximum jump height and ground reaction force simultaneously. The first objective of this research is to identify an appropriate skeleton tracking technology to accurately track counter movement jump and squat jump. In this research a low-cost depth camera named Orbbec Astra Pro and a pose estimation model named moveNet were evaluated for skeleton joint tracking. Based on the accuracy, the moveNet pose estimation model was chosen for skeleton joint tracking of athletes. The next objective of this study is to investigate how skeleton joint data can be used to measure body assessment parameters used in strength and power estimation. Initially, knowledge about clinically and medically accepted procedures for determining power and strength was obtained through literature. Then transformations were used to convert clinical approaches to a method that used skeleton joint variation with time. Two-rule based models were proposed based on the derived transformations to identify athletes performance parameters and biomechanics respectively. After fine tuning the biomechanical model, an accuracy of 95.8% and a mis-classification rate of 4.2% was achieved. Hence, better accuracy was able to be achieved in the biomechanical model. An additional rule was added to the model based on the domain expert's feedback. In the performance parameter model, the maximum jump height was estimated with a standard error deviation of 1.7 cm. However, the standard error deviation is comparatively higher than the approaches proposed by O'Reilly *et al.* (2017) and Kranz *et al.* (2013). In this study only the athlete's jump height could be evaluated due to the unavailability of force plates in local context to test GRF and other two parameters.

CONCLUSION

Identification of body power and strength is a widely discussed topic in the field of sports science. The most frequently used vertical jump tests to assess body capacities are countermovement jump and squat jump. This research was focused on identifying athlete body power and strength using skeleton joint tracking which can be handled at the athlete's own pace. The system demonstrates a high level of accuracy in identifying athlete biomechanics, achieving 91.7% accuracy for countermovement jumps and 95.8% accuracy for squat jumps. This shows that the model is reliable and effective in analyzing and distinguishing the biomechanics of the mentioned jumps performed by athletes. The model's ability to measure maximum jump height with a standard error of 0.88 cm suggests a high degree of precision. This study also gives insights into different athletes showing different body power and strength levels based on the sport. A clear classification can be observed in body power and strength levels of netball players vs hockey players.

Furthermore, this model can be used in connection with learning approaches such as machine learning along with some additional data such as body temperature, and heart rate to identify more hidden patterns and information in athletes' performances. Future work should explore methods to enhance the 3D spatial accuracy of the model for better capturing and analyzing the athlete's movements. Additionally, the proposed system can be developed into a user application that is compatible with a portable device such as a laptop or a smartphone.

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